Behavioral Biases in Marketing: Conducting Choice Experiments with Inattentive Consumers and Modeling their Decisions

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Abstract

A central task of marketing is understanding consumer preferences and uncovering consumer heterogeneity. A range of critical decisions, e.g., new product development, market segmentation and targeting, or pricing, rest upon accurate estimation of consumer preferences. Marketing literature has mainly focused on the development of models and estimation procedures that allow uncovering consumer preference heterogeneity. However, consumers are different not only in their tastes but also in the way they make purchase decisions. In particular, there is a considerable amount of evidence that consumers ignore available information on choice alternatives and product attributes when making purchase decisions.

While efforts have been made to develop models accounting consumers' inattention to alternatives, models accounting for consumers' inattention to attributes remains an understudied area in marketing literature. Whereas, which attributes consumers truly consider when buying products is of high importance for practitioners to understand and leverage.

The overall objective of this dissertation is to enhance our understanding of consumers' inattention to attributes when making choices. It aims to 1) examine the prevalence of such inattention across numerous contexts and settings, 2) investigate and extend the approaches that explicitly accommodate such behavior, 3) understand potential biases that may arise, and 4) demonstrate managerial implications when such behavior is neglected.

The findings from a broad set of applications suggest that consumers ignore a substantial amount of available attribute information across various contexts (e.g., product categories) and settings (e.g., of high or low complexity). Second, we establish that choice models explicitly accounting for such behavior and, additionally, leveraging supplementary data such as eye tracking, result in better in- and out-of-sample fit. Third, neglecting such behavior leads to significant biases, the direction and the magnitude of which depend on the type of the attribute (i.e., whether a particular direction of preferences can be expected) and the share of consumers ignoring this attribute. As a result, managers may make suboptimal pricing and targeting decisions.

Zusammenfassung

Eine zentrale Aufgabe des Marketings ist es, die Präferenzen von Konsumenten zu verstehen und die Heterogenität der Konsumenten aufzudecken. Eine Reihe kritischer Entscheidungen, z.B. bei der Neuproduktentwicklung, der Marktsegmentierung und dem Targeting oder der Preisgestaltung, beruhen auf der genauen Einschätzung der Konsumentenpräferenzen. Die Marketingliteratur hat sich bisher auf die Entwicklung von Modellen und Schätzverfahren konzentriert, die es ermöglichen, Heterogenität der Konsumentenpräferenzen aufzudecken. Konsumenten unterscheiden sich jedoch nicht nur in ihrem Geschmack, sondern auch in der Art und Weise, wie sie Kaufentscheidungen treffen. Insbesondere gibt es eine hohe Evidenz dafür, dass Konsumenten verfügbare Informationen über Auswahlalternativen und Produkteigenschaften bei Kaufentscheidungen ignorieren.

Es wurden zwar Anstrengungen unternommen, Modelle zu entwickeln, die die Unaufmerksamkeit der Konsumenten gegenüber Alternativen berücksichtigen, aber Modelle, die die Unaufmerksamkeit der Konsumenten gegenüber Produkteigenschaften berücksichtigen, sind in der Marketingliteratur nach wie vor ein noch wenig untersuchtes Gebiete. Die Frage, welche Produkteigenschaften Konsumenten beim Kauf von Produkten wirklich berücksichtigen, ist für die Praxis von großer Bedeutung, um sie zu verstehen und zu nutzen.

Das Ziel dieser Dissertation ist es, unser Verständniss für die Unaufmerksamkeit der Konsumenten gegenüber Produkteigenschaften bezüglich Entscheidungen zu verbessern. Es geht darum, 1) die Verbreitung einer solchen Unaufmerksamkeit in verschiedene Kontexten zu untersuchen, 2) die Methoden, die ein solches Verhalten explizit berücksichtigen, zu untersuchen und zu erweitern, 3) potenzielle Verzerrungen in Parametern zu verstehen und 4) Implikationen für das Management abzuleiten.

Die Ergebnisse aus einer umfassenden Reihe von Anwendungen legen nahe, dass Konsumenten in verschiedenen Kontexten (z.B. Produktkategorien) und Settings (z.B. von hoher oder niedriger Komplexität) eine Menge an verfügbaren Informationen bezüglich Produkteigenschaften ignorieren. Zweitens, Entscheidungsmodelle, die ein solches Verhalten explizit berücksichtigen und zusätzlich weitere Daten wie z.B. Eye-Tracking nutzen, zu einem besseren In- und Out-of-Sample-Fit führen.

Drittens, führt die Missachtung eines solchen Verhaltens zu signifikanten Verzerrungen, deren Richtung und Größe von der Art des Merkmals (d.h., ob eine bestimmte Richtung der Präferenzen erwartet werden kann) und dem Anteil der Konsumenten, die dieses Merkmal ignorieren, abhängt. Infolgedessen kann es dazu kommen, dass Manager keine optimalen Preis- und Targeting-Entscheidungen treffen.

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Abbreviations

ANA	Attribute non-attendance
BIC	Bayesian information cirterion
CBC	Choice-based conjoint
EAA	Endogeneous attribute attendance
IAA	Independence of attribute attendance
LL	Log-likelihood
MEAA	Mixed endogeneous attribute attendance
MNL	Multinomial logit
MMNL	Mixed multinomial logit
MMMNL	Mixed-mixed multinomial logit
PWYW	Pay what you want
RFID	Radio-frequency identification
RUM	Random utility maximization
SD	Standard deviation
va	Visual attention
WOM	Word-of-mouth
WTA	Willingness-to-accept
WTP	Willingness-to-pay

1 | Introduction

A central task of marketing is to understand consumer preferences. In this context, heterogeneity plays a particularly important role (Allenby and Rossi 1998). It is the heterogeneity that facilitates product differentiation, market segmentation and targeting, as well as price discrimination (Allenby and Rossi 1998). A range of critical decisions related to marketing mix elements – product, price, promotion, and place, rest on accurate estimation of consumer preferences (Keane and Wasi 2013). Hence, many efforts in discrete choice models, which are used for measuring preferences and supporting the outlined marketing decisions, focused on the development of models and estimation procedures that allow uncovering the heterogeneity of consumer preferences (Russell 2014). When data on consumer characteristics, e.g., demographics or past purchase history, are available, these can be used to identify the "observed" consumer heterogeneity (e.g., Kalyanam and Putler 1997; Guadagni and Little 1983). Alternatively, "unobserved" heterogeneity models can be utilized (Allenby and Rossi 1998). In these models, it is typical in marketing literature to assume that preference parameters come from a discrete distribution, often termed as a finite mixture or latent class model (e.g., Kamakura and Russell 1989), or a continuous (e.g., multivariate normal) distribution (e.g., Allenby and Ginter 1995; Erdem 1996). Further advances in discrete choice models primarily focused on allowing for even more flexible forms of preference heterogeneity to accommodate potential multi-modal parameter distribution in the population (e.g., Keane and Wasi 2013; Voleti et al. 2017).

However, heterogeneity can stem not only from differences in consumer preferences but also from the way they make purchase decisions (Kamakura et al. 1996). To be more explicit, in any model, we make certain assumptions on how consumers behave. Discrete choice models typically build upon the behavioral theory of the random utility maximization (RUM; McFadden 1974)[1]. RUM relies on the standard assumptions originating from neoclassical microeconomic theory. In particular, consumers are assumed to take into account all the available information, apply a compensatory decision rule[2], and maximize their utility. The latter is specified as

[1] This theory originates from the seminal work of Thurstone (1927) and Luce (1959).

[2] Compensatory decision rule implies that the negative aspects on one product attribute can be balanced out by positive aspects on another attribute

a linear additive function of product attributes (deterministic component) and an error term (random component).

Empirical research in marketing, behavioral decision-making, and behavioral economics has documented many cases of "behavioral biases," i.e., violations of the assumptions of the standard economic theory (Thaler 2016) that also apply to the RUM model. Ample observational and experimental evidence of violations of standard economic assumptions has enabled a classification framework of these biases into three broad groups: nonstandard preferences, nonstandard beliefs, and nonstandard decision-making (DellaVigna 2009). The class of nonstandard preferences refers to violations of the standard economic assumptions that are related to the utility function (e.g., time-inconsistent preferences or reference-dependence). The class of nonstandard beliefs includes biases that emerge in the presence of uncertainty and violate the standard economic assumptions on how consumers form beliefs. Finally, the class of nonstandard decision-making addresses observations of non-utility-maximizing behavior, including violation of the assumption of full and perfect information processing. As this thesis will establish, behavioral biases affect consumers throughout all the phases of purchase decision-making – need recognition, pre-purchase, purchase, and post-purchase phases. It is generally accepted that these four phases capture the key aspects of consumers' activities during the process of product purchase (e.g., Lee et al. 2018). The primary focus of this thesis is on nonstandard decision-making, in particular limited attention, and its impact on consumers in the purchase phase.

It is well established that consumers have limited cognitive abilities and do not process all the available information (Payne et al. 1992). Many studies in marketing provide evidence that increase in complexity and the amount of available information (including an increase in the number of choice alternatives and product attributes) may lead to information overload (Malhotra 1982), prompting people to apply simplifying heuristics (Payne et al. 1992), ignore information (Shi et al. 2013), or defer from making a choice altogether (Dhar 1997). Hence, limited attention is a direct violation of the assumption of full information processing in the RUM model and may lead to choices that are inconsistent with utility maximization assumption (Simon 1955).

In marketing literature, much consideration was given to developing models that account for consumers' limited attention to available alternatives. In particular, these models commonly assume that consumers first restrict the number of alternatives they consider, and it is within this "consideration set" of alternatives that they make purchase decisions in accordance to the assumptions of the RUM model (e.g., Bronnenberg and Vanhonacker 1996; Swait and Ben-Akiva 1987). A core element of these models is how these consideration sets are formed. For example, given actual purchase data (e.g., scanner panel), the inclusion of various alternatives into consideration set can been conditioned on marketing mix variables as well as past purchase data (e.g., Bronnenberg and Vanhonacker 1996; Mehta et al. 2003; Draganska and Klapper 2011). Also, methods have been proposed that utilize only observed choice data (e.g., Swait and Ben-Akiva 1987).

While the topic of limited attention to alternatives has and continues to draw much attention (e.g., see Fosgerau et al. 2016; Joo 2018), choice models incorporating limited attention to attributes remain rather scarce in marketing literature. Driven by consumers' motivations and beliefs (Gilbride et al. 2006) or cognitive constraints (Bettman et al. 1998), consumers may find different product attributes relevant when making purchase decisions. For example, some consumers may prefer fairtrade products. For others, the presence of the fairtrade label may not affect the purchase decision in any way (i.e., the effect of the fairtrade label for them is precisely zero). However, typical models of consumer preference heterogeneity mentioned above are not well equipped to deal with such behavior (Gilbride et al. 2006). As they pool data across the sample, they may not be able to distinguish between low (i.e., close to zero) and zero effect (e.g., Gilbride et al. 2006; Hess et al. 2013). As highlighted earlier, this can have repercussions on many crucial managerial decisions.

Nevertheless, only several studies in marketing literature explicitly examine the importance of incorporating consumers' inattention to product attributes in discrete choice models. Other applications stem from adjacent fields of operation research, transportation science, and health economics. Consumers' inattention to attributes has been conventionally termed as "attribute non-attendance" (ANA) in these adjacent fields (hereafter this terminology is adopted, ANA and consumers' inattention to attributes are used as synonyms). However, findings and insights in these applications are not always directly transferable to the marketing context, and overall many questions remain open. In the remaining part, the specific research gaps are identified, which represent the more specific research agenda of this dissertation.

First, in terms of choice context, methods accounting for ANA have been applied in marketing applications for products sold on e-commerce websites (Currim et al. 2015), durable products[3] (Gilbride et al. 2006), coffee makers (Meißner et al. 2011), as well as digital cameras (Maldonado et al. 2015; Maldonado et al. 2017). Due to the limited number and variety of applications, it remains unclear how prevalent ANA is in other contexts (e.g., non-durable product choice) and settings (e.g., high vs. low complexity settings). As a consequence, it is not apparent how critical it is to explicitly accommodate such behavior in choice models for these different cases. Applications in other fields include such contexts as route choice (e.g., Hess et al. 2013) or prescription drug choice of doctors (Hole et al. 2013), which are

[3] The exact product category and product attributes are unknown in both Currim et al. (2015) and Gilbride et al. (2006) due to the proprietary nature of the data.

quite different from typical marketing contexts. The first aim of this dissertation is, therefore, to examine the prevalence of ANA in various marketing contexts and settings.

Second, we still have limited understanding of how ANA affects the uncovered preference distribution and the direction and the magnitude of biases that may arise when ANA is neglected in the model. In general, several approaches were proposed that explicitly allow for ANA and can infer it using only choice data. Some of these methods primarily focus on out-of-sample predictions (e.g., Maldonado et al. 2015; Maldonado et al. 2017)[4]. As a result, we do not learn much from these applications about the uncovered distribution of preference parameters. Other methods include the heterogeneous variable selection model proposed by Gilbride et al. (2006) and the latent class approach of, e.g., Hess et al. (2013) and Hole et al. (2013), which is closely related to consideration set models of Swait and Ben-Akiva (1987). In the latent class approach, latent classes are defined a priori describing every possible combination of attributes that may be ignored by consumers. Both the heterogeneous variable selection model and the latent class approach can simultaneously account for ANA and preference heterogeneity[5].

Overall, findings suggest that choice models that fail to account for ANA result in biased estimates. This has severe implications for all the subsequently computed measures such as willingness to pay (WTP) or relative importance of attributes (e.g., Gilbride et al. 2006; Hess et al. 2013; Hole et al. 2013). In particular, all these applications report that the mean estimates of preference distribution are biased towards zero. Such a result is intuitive. As some consumers ignore particular attributes and, therefore, have a true effect of zero, they pull the average effect closer to zero. By contrast, the direction and the magnitude of the biases in the estimates of the variance of preference distribution are not necessarily obvious. Applications in transportation science, which predominantly include attributes that should have a clear preference direction (e.g., price or time), report an upward bias, i.e., overstatement of the amount of heterogeneity (e.g., Collins 2012). In marketing contexts, many of the attributes (e.g., brand, color, or flavor) allow firms to differentiate their products horizontally (Draganska and Jain 2006). For such attributes, the parameter distribution can span both positive and negative domains[6]. Existing applications do not inform us what the direction and the

[4]More explicitly, Maldonado et al. (2015) and Maldonado et al. (2017) deploy feature selection tools from machine learning literature, in particular support vector machine (SVM) algorithm, to infer the attributes ignored by consumers. The proposed approach performs better in out-of-sample predictions than the standard model, which assumes full information processing.

[5]These models are very similar. However, in contrast to Hess et al. (2013) and Hole et al. (2013), Gilbride et al. (2006) utilize Bayesian estimation methods. In the comparison of the two approaches, Scarpa et al. (2009) did not find significant differences in the results. Therefore, later on, this thesis adopts the latent class approach.

[6]For instance, some consumers may prefer, e.g., a pink smartphone, while others not. As a result, we could expect to find both positive and negative parameters for the color pink.

magnitude of the biases in parameter estimates would be if some consumers ignore these attributes. Hence, this dissertation aims to investigate how ANA affects preference distribution, the direction and the magnitude of the biases that may arise when the choice model does not account for ANA, and the subsequent effects on managerial decisions. Third, it remains an open question if the proposed models can be further augmented to understand individual-level behavior better. For example, Hole et al. (2013) and Collins et al. (2013) suggest using respondents' stated measure of ANA as a covariate in the latent class approach for modeling consumer inattention to attributes. Nevertheless, the objectivity and reliability of this measure remain an issue. Eye tracking data, on the other hand, is considered to be more objective (Meißner and Oll 2017). The measures derived from eye tracking have been used before as deterministic indicators of ANA (e.g., Meißner et al. 2011; Balcombe et al. 2015). An open question remains: how useful are such measures as covariates within a latent class approach? This dissertation, therefore, aims to investigate the added value of augmenting models that explicitly account for ANA using measures derived from eye tracking data.

In summary, the overall objective of this dissertation is to enhance our understanding of consumer inattention to product attributes when making purchase decisions. More specifically, this thesis aims to cover the gaps in the marketing literature outlined above through a collection of three articles. Figure 1.1 illustrates the overall structure of the thesis.

The first article (Chapter 2) titled "Behavioral Biases in Marketing" is a joint work with Katharina Dowling, Daniel Guhl, Daniel Klapper, Lucas Stich, and Martin Spann published in the *Journal of the Academy of Marketing Science* (see Dowling et al. 2020). It is a conceptual paper, which provides a comprehensive review of behavioral biases in marketing. While the extensive marketing literature documents consumers' nonrational behavior, behavioral biases might not always be consistently termed or formally described. Hence, the review article utilizes a commonly used classification of biases in behavioral economics (i.e., nonstandard preferences, nonstandard beliefs, and nonstandard decision-making; DellaVigna 2009) outlined before and examines their impact across different phases of consumer purchase decision-making. This organizing framework allows to identify connections and differences within and across categories in both dimensions, as well as outline varying degrees of influence of particular classes of biases in particular phases of consumer decision-making. The article finds a rich literature covering behavioral biases during the pre-purchase and purchase phases, whereas the marketing literature dedicated to behavioral biases during the need recognition and post-purchase phases is relatively scarce. Moreover, the findings suggest that particularly nonstandard decision-making influences all the phases. However, a wider variety of specific biases

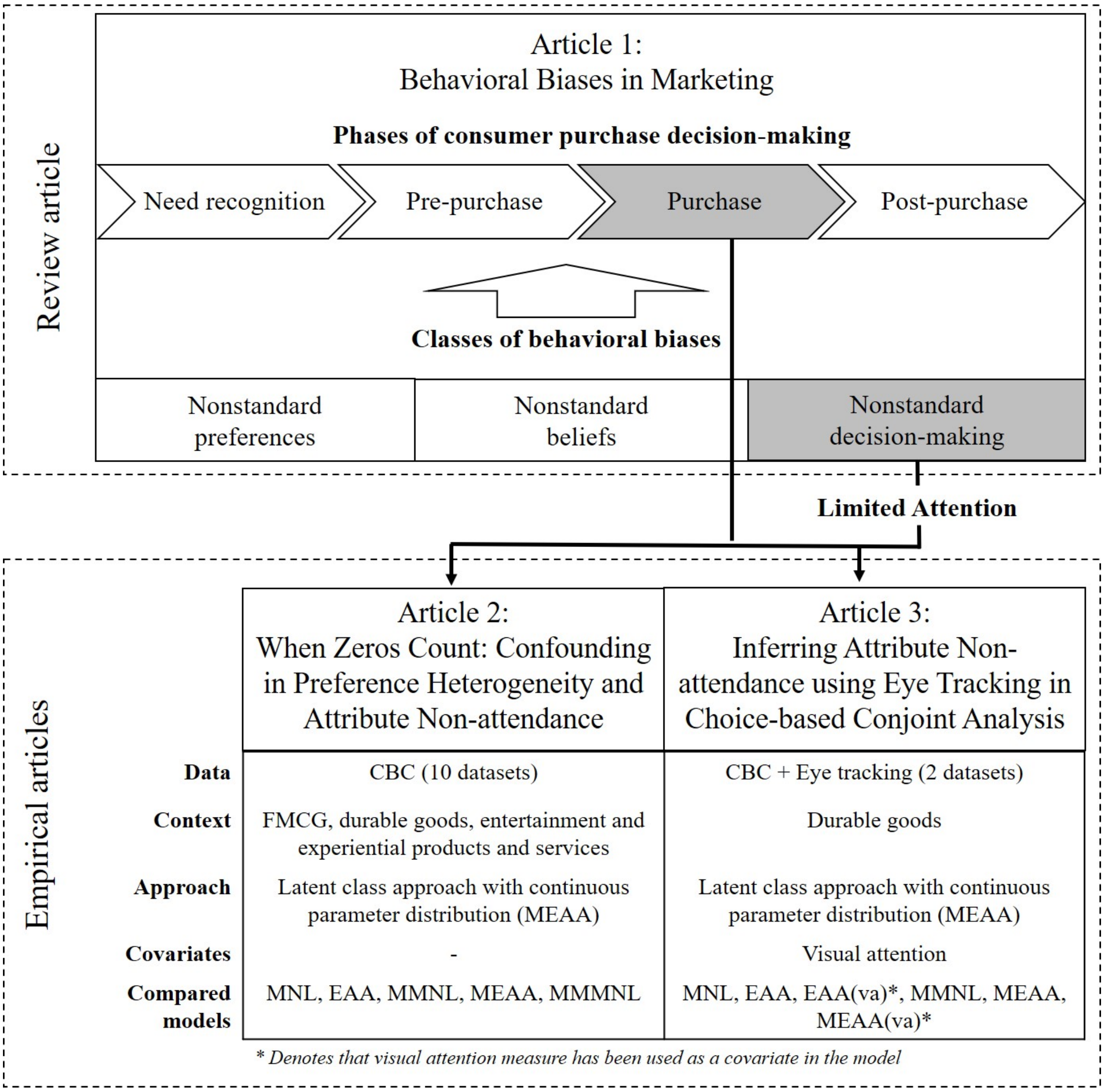

Figure 1.1. Overall structure of the thesis

in this class, including framing, context effects, and especially limited attention, affect consumers in the purchase phase.

As previously mentioned, some aspects of the limited attention and its impact on consumers in the purchase phase are understudied in marketing literature. Hence, the following two empirical articles aim to cover this gap and focus on this particular behavioral bias in this particular phase of purchase decision-making. In Figure 1.1, this is represented through the grey highlighting of the corresponding phase and class of bias in the framework of Article 1. The arrows illustrate the link between Article 1 and the two empirical articles. The two empirical articles include Article 2 (Chapter 3) titled "When Zeros Count: Confounding in Preference Heterogeneity and Attribute Non-attendance," which is a working paper with Daniel Guhl and Friederike Paetz, and Article 3 (Chapter 4) titled "Inferring Attribute Non-attendance using Eye Tracking in Choice-based Conjoint Analysis" – a joint work with Daniel Guhl and Daniel Klapper published in the *Journal of Business Research* (see Yegoryan et al. 2020).

Articles 2 and 3 share some similarities (see Figure 1.1). Both articles use data from a choice-based conjoint (CBC) study. Article 2 uses a broad set of 10 different datasets that vary in terms of the financial risk or stakes of the decision, as well as the number of attributes presented to the respondents (i.e., the complexity of the decision). This broad set of applications allows examining the persistence of ANA in different contexts and settings. Two applications in Article 3 involve choices of durable goods (coffee-makers and laptops). By contrast, here, a combination of choice data from a CBC and simultaneously collected eye tracking data is utilized.

Both articles have a methodological focus and adopt the latent class approach with a continuous parameter distribution across classes suggested by Hole et al. (2013) for simultaneously modeling ANA and preference heterogeneity. Hole et al. (2013) refer to it as mixed endogenous attribute attendance (MEAA) model. Both articles compare this model with several benchmarks that include choice models that account for neither preference heterogeneity nor ANA (i.e., multinomial logit (MNL) model), only preference heterogeneity (i.e., mixed multinomial logit (MMNL) model), and only ANA (endogenous attribute attendance (EAA) model; see Hole 2011). Article 2 further compares the MEAA model with a mixture of normals multinomial logit (MMMNL; see, e.g., Keane and Wasi 2013) model, which allows incorporating more flexible forms of preference distribution. Through the comparison of these models, Article 2 investigates the confounding between preference heterogeneity and ANA. As previously outlined, models that ignore ANA may falsely identify consumers who ignore the particular attribute as having low sensitivity (Gilbride et al. 2006; Hole et al. 2013). On the other hand, models that ignore preference heterogeneity may falsely classify consumers with low sensitivity as having zero sensitivity, i.e., ignoring the particular attribute (Hess et al. 2013; Hole et al. 2013). A particular focus of Article 2 is on investigating how ANA affects the recovery of preference distribution and examining the direction and the magnitude of resulting biases in parameter estimates. Moreover, considering the broader set of empirical applications, Article 2 provides insights on which situations and for which research goals the models accommodating ANA are necessary and when the application of the standard model may be sufficient.

Article 3 proposes a further extension of the latent class approach. More specifically, models accounting for ANA are augmented using a measure of visual attention derived from eye tracking data. This method allows linking visual attention to attribute attendance and subsequently choice. The augmented models are then compared to their counterparts (i.e., EAA and MEAA) to investigate the added value of eye tracking in this framework in helping to understand individual-level behavior.

First, across the two empirical articles, the dissertation establishes that consumers ignore attribute information across all 12 empirical applications. They do so not only in categories that involve low financial risk (e.g., buying orange juice) but also in high-stake decisions (e.g., choosing a holiday destination or investing in a laptop). ANA occurs not only in high complexity settings (e.g., with 5-8 attributes) but also in low complexity settings (e.g., with only 3-4 attributes). In general, the results indicate that consumers tend to ignore attribute information more when low financial risks are associated with a purchase decision, and in more complex settings with a higher number of attributes.

Second, regarding the direction and the magnitude of the biases, the results suggest that biases in parameter estimates do indeed occur when choice models do not accommodate either preference heterogeneity or ANA. In line with previous literature, the mean estimates are found to be predominantly biased towards zero when neglecting ANA in the choice model. Contrary to previous literature, cases of over- and underestimation of the amount of heterogeneity are found when choice models fail to account for ANA. The magnitude and the direction of the bias appear to depend on the amount of ANA and the location of the preference distribution with respect to zero. We find that when the distribution is located further away from zero (e.g., in the cases of attributes like price or fairtrade label), we commonly observe an overestimation of the variance of preference distribution when the choice model neglects ANA. On the other hand, the estimates of variance are predominately understated when the preference distribution spans across both positive and negative domain. For example, such cases are found for attributes like brand. Consequentially, biases in estimates yield substantial differences in the distribution of WTP and measures of the relative importance of attributes. Using a model that neglects ANA, may lead to suboptimal pricing and targeting decisions.

Third, the results establish that visual attention measures derived from eye tracking significantly help the identification of different attribute processing strategies used by consumers and improve model fit. Such model augmentation is useful for a deeper understanding of how visual attention influences choice and can be leveraged for one-to-one targeting. Moreover, while all in all, we find that visual attention to a particular attribute increases the likelihood of using this attribute in the decision-making, the same amount of visual attention results in different attendance probabilities across attributes. Therefore, the model may capture the effects of the presentation format of the attributes and choice tasks in general.

In summary, this dissertation contributes to several streams of research, including behavioral biases in general and limited attention in particular, discrete choice modeling, and eye tracking literature. It provides further insights on the prevalence of ANA in various contexts and settings, highlights the importance of accommodating such behavior in choice models, enhances our understanding of potential biases that may arise, and demonstrates managerial implications when the analyst neglects consumer inattention to attributes.

2 | Behavioral Biases in Marketing [1]

Katharina Dowling, Daniel Guhl, Daniel Klapper, Martin Spann, Lucas Stich, and Narine Yegoryan

Abstract

Psychology and economics (together known as behavioral economics) are two prominent disciplines underlying many theories in marketing. The extensive marketing literature documents consumers' nonrational behavior even though behavioral biases might not always be consistently termed or formally described. In this review, we identify and synthesize empirical research on behavioral biases in marketing. We document the key findings according to three classes of deviations (i.e., nonstandard preferences, nonstandard beliefs, and nonstandard decision-making) and the four phases of consumer purchase decision-making (i.e., need recognition, pre-purchase, purchase, and post-purchase). Our organizing framework allows us to (1) synthesize instructive marketing papers in a concise and meaningful manner and (2) identify connections and differences within and across categories in both dimensions. In our review, we discuss specific implications for management and avenues for future research.

Keywords

Marketing, Consumer purchase decision-making, Behavioral economics, Behavioral biases, Review

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[1] This chapter is published in Dowling, K., Guhl, D., Klapper, D., Spann, M., Stich, L., and Yegoryan, N. (2020). Behavioral Biases in Marketing. *Journal of the Academy of Marketing Science*, 48: 449–477. DOI: https://doi.org/10.1007/s11747-019-00699-x.

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2.1 Introduction

For several decades, research in the field of behavioral economics (i.e., the mixture of psychology and economics) has provided ample evidence showing that individual decisions are often systematically biased and do not confirm the forecasts of the standard economic theory (Thaler 2016). Such "behavioral biases" represent deviations from the standard economic model, which assumes that people are rational, i.e., have stable preferences, maximize expected utility (defined over final payoffs), exponentially discount future utility, process information in a Bayesian manner, and are purely self-interested (Rabin 2002). In line with contemporary research in economics, this paper refers to the standard economic model as a clearly defined benchmark (i.e., a model) for making predictions about and analyzing observed human behavior (Rabin 2002). Behavioral scientists have successfully established new theories that formalize and can explain behavior that deviates from the standard economic model.

In business research, particularly in the domains of marketing and finance[2], the use of psychological theory has a long history and is deeply rooted in the study of human behavior. In fact, precisely predicting human behavior to inform marketing decisions is a key objective of marketing. Marketing has always been concerned with explaining the motivations and belief systems of buyers and sellers; however, in contrast to (behavioral) economics, marketing lacks a uniform framework and terminology (Conick 2017). Furthermore, although economics and psychology are the two most influential disciplines underlying marketing (Ho et al. 2006), to date, no review has documented empirical findings by focusing solely on behavioral biases in marketing. Nonetheless, marketers could benefit from drawing more extensively from the many theoretical explanations provided by behavioral economics, and economists could benefit from more closely following developments in marketing (e.g., developments exploiting the availability of rich consumer data documenting instances of nonrational behavior)[3].

In this paper, we aim to integrate research from behavioral economics and marketing. The objectives of this paper are to identify and synthesize marketing research that analyzes behavior deviating from neoclassical predictions and to map these findings onto a structure involving elements of marketing and economics. We focus on evidence from both the field and the laboratory[4]. We aim to identify

[2]A review documenting empirical findings in the field of behavioral finance is provided by Barberis and Thaler (2003).

[3]http://evonomics.com/behavioraleconomics-neglect-marketing

[4]In contrast to the typical context-free laboratory experiments performed in the field of economics, laboratory studies in the field of marketing usually involve a marketing context and may, therefore, provide interesting insight into how consumers and firms might behave under different circumstances.

commonalities, differences, and nonobvious connections between the two fields (Palmatier et al. 2018).

The contribution of our review paper is two-fold. First, we provide a structured review of how behavioral biases studied in marketing contexts and published in marketing outlets can affect the four phases of consumer purchase decision-making: (1) need recognition, (2) pre-purchase, (3) purchase, and (4) post-purchase. It is widely accepted that these four phases capture the key aspects of consumers' activities during the process of product purchase, ranging from early theoretical models of consumer behavior (e.g., Howard and Sheth 1969) to current descriptions of consumer decision-making (e.g., Lee et al. 2018). We focus on three theoretically substantiated classes of biases (i.e., nonstandard preferences, nonstandard beliefs, and nonstandard decision-making; DellaVigna 2009) rather than on individual biases and synthesize their effects on consumers during each phase of purchase decision-making. Using this framework, we analyze how each of the three classes can influence each of the four phases. We identify and discuss nonobvious connections and different levels of importance of the three classes within and across phases. In addition, we introduce marketing researchers to the terminology employed in the field of behavioral economics and, thus, may help them better navigate the extensive list of documented biases in this field. Moreover, we provide scholars from the field of behavioral economics easy access to the rich marketing literature related to applied empirical research.

Second, we provide specific implications for marketing practice and discuss potential directions for future research. We debate (1) behavioral biases in digital and digitally enhanced environments, (2) behavioral biases in the context of big data and data analytics, (3) behavioral biases and marketing instruments, and (4) potential negative consequences of exploiting behavioral biases. Moreover, we propose and discuss five streams of future research. We identify research directions and opportunities related to (1) the phases of consumer purchase decision-making and the classes of behavioral biases, (2) marketing instruments, (3) methodology, (4) new technologies and business models, and (5) competition, learning, and persistence.

The paper's structure reflects the goal of combining marketing and behavioral economics. The conceptual framework described in the following section introduces the four phases of consumer purchase decision-making, outlines the three classes of behavioral biases, and explains our research process. Subsequently, using particularly instructive papers, we illustrate how each of the three classes can influence each of the four phases. We discuss connections and differences within and across phases. Finally, we derive specific implications for practice and identify avenues for future research. The paper ends with a summary and conclusion.

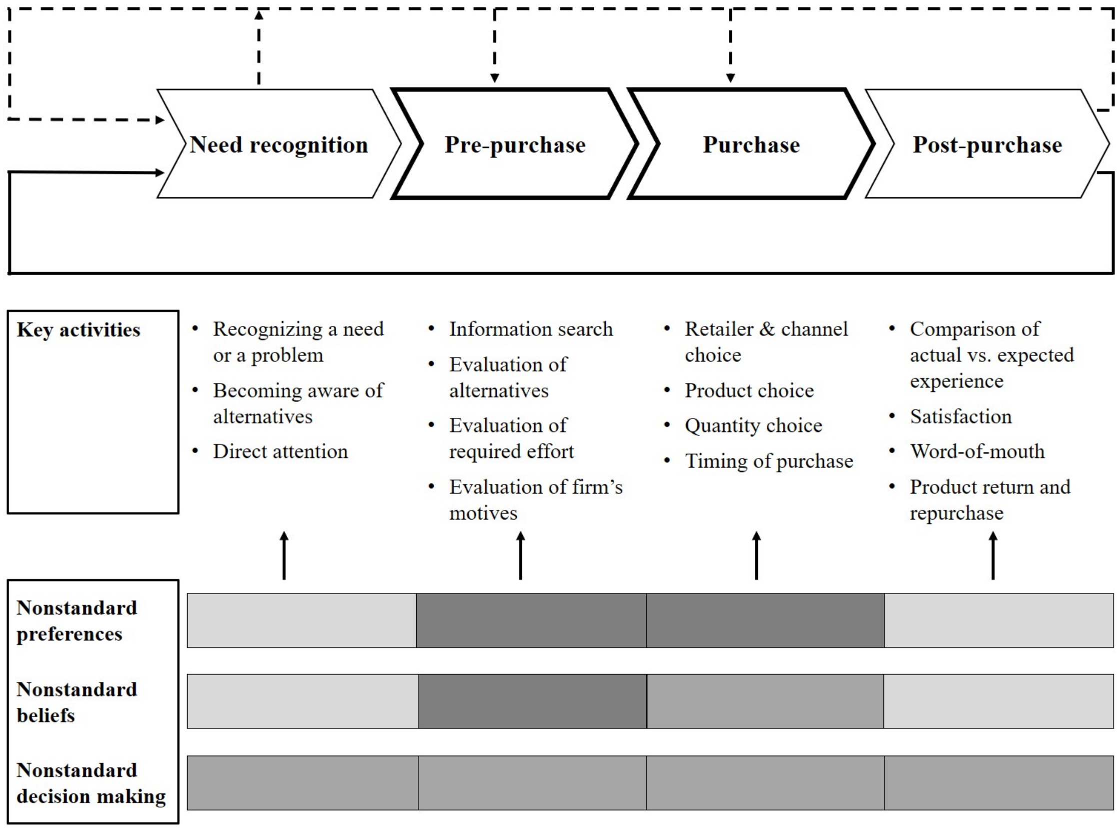
2.2 Conceptual Framework and Research Process

In this section, we present and discuss the conceptual framework of our review. Figure 2.1 shows the four phases of consumer purchase decision-making, including the different key activities of each phase, and how these are influenced by the three classes of behavioral biases. We also embed key insights from our review regarding differences across phases and classes.

The four phases do not always follow each other in a linear, sequential way (e.g., Lemon and Verhoef 2016). As indicated by the dashed arrows above the four phases in Figure 2.1, consumers' shopping journeys can be nonlinear. For example, in impulse buying situations, consumers may recognize a need in the need recognition phase and then directly proceed to the purchase phase without any pre-purchase activities. Moreover, consumers may iterate through the four phases multiple times in the case of repeat purchases, as indicated by the solid arrow underneath the four phases in Figure 2.1.

Reviewing and studying all four phases provides a more detailed understanding of behavioral biases in marketing. The marketing literature often focuses on the pre-purchase and purchase phases; hence, insights into these phases and related biases occur more frequently (indicated by the bold outlines). Nevertheless, since behavioral biases may originate during any phase, only exploring the two core phases may lead to an incomplete understanding of consumers' purchase decision-making. For example, consumers frequently become aware of a need through advertising (need recognition phase), but consumers may systematically misinterpret the advertised information, which may result in biased decisions in the purchase phase. Similarly, behavioral biases (e.g., the endowment effect) can influence consumers' product-return decisions in the post-purchase phase. Given that biases can span multiple phases or that several biases can interact across phases, it is necessary to consider all four phases of consumer purchase decision-making.

We propose that the three classes of behavioral biases have different levels of importance across the four phases, as highlighted in Figure 2.1 (in increasing importance from light to dark gray). Nonstandard preferences are particularly important during the pre-purchase and purchase phases since consumers' preferences are relevant for both the evaluation of and search for alternatives as well as the quantity and timing of the actual purchase. We observe a similar pattern for nonstandard beliefs, with an even greater relevance of the pre-purchase phase. Nonstandard beliefs play an important role when consumers must make predictions about their future behavior, which usually involves uncertainty. This is especially relevant in the pre-purchase phase, in which many of the activities require estimates under uncertainty (e.g., usage estimation). Nonstandard decision-making affects all phases of consumer purchase decision-making. Particularly prevalent biases within



Notes: The term "nonstandard" is adopted from DellaVigna (2009) and refers to deviations from the standard model in economics, divided into preferences, beliefs, and decision making. The marketing literature often focuses on the pre-purchase and purchase phases, and hence, insights into these phases and related biases are more frequent (indicated by the bold outlines). Consumers may skip phases (dashed arrows above the four phases) and/or iterate through the phases multiple times (solid arrow underneath the four phases). The three classes of behavioral biases have different levels of importance across the four phases (increasing importance from light to dark grey).

Figure 2.1. Conceptual framework

the class of nonstandard decision-making, such as framing effects, are especially important during the pre-purchase and purchase phases but to a lesser extent in their adjacent phases. However, social pressure and persuasion matter during the need recognition phase (e.g., recognizing a need through advertising or peers), and emotions are particularly relevant in the post-purchase phase (e.g., word-of-mouth (WOM) behavior). In the following, we introduce and discuss the four phases of consumer purchase decision-making and the three classes of behavioral biases in detail and summarize our research process.

2.2.1 Phases of Consumer Purchase Decision-Making

The process of consumers' purchase decision-making is often presented as four distinct phases, including (1) need recognition, (2) pre-purchase activities, (3) purchase decision, and (4) post-purchase activities (e.g., Yadav et al. 2013). Although we are well aware that customer journeys are affected by an evolving retailing landscape (e.g., technological and structural changes; Lee et al. 2018), we believe that the core states of the purchase process remain valid.

2.2.1.1 Need Recognition

During the need recognition phase, the consumer recognizes a problem or need due to an internal signal (e.g., thirst) or an external signal (e.g., advertisement; Yadav et al. 2013; Lee et al. 2018). During this phase, consumers become aware and intrigued by a particular brand, product (category), or some aspect of the shopping environment. The consumer's social environment also often plays an essential role in influencing and determining the consumer's perceived needs. For example, we learn about products by observing other people (offline or online), which may subsequently prompt us to adopt the same products.

2.2.1.2 Pre-purchase Activities

During the pre-purchase phase, consumers engage in information search and evaluation of alternatives (Lee et al. 2018; Yadav et al. 2013). This process can involve browsing for products or actively searching for a specific product. During this phase of the decision process, consumers deliberatively assess the various products in their consideration set and how such products align with their needs, wants, and objectives. Consumers also evaluate the effort (i.e., money, time, and energy) required to acquire the product. If the effort is considered excessive relative to the benefits, consumers may choose not to proceed with a purchase during the following phase. In addition to the specific product, consumers evaluate inferred firm motives (e.g., the perception of price fairness).

2.2.1.3 Purchase Decision

During the purchase decision phase, consumers make decisions regarding whether to make a purchase, which and how many product(s) to buy, which seller from whom to purchase, the timing of the purchase, and other terms and conditions related to the purchase (Lee et al. 2018; Yadav et al. 2013). This phase also includes potential waiting time, such as for products purchased online to be shipped and delivered. In some purchases (i.e., impulse buying), consumers may directly jump to this phase (see also the meta-analytic review of Iyer et al. 2019 in this special issue).

2.2.1.4 Post-purchase Activities

After a purchase, consumers use the product and often compare their actual consumption experience with their expectations (Lee et al. 2018; Yadav et al. 2013). Consumers assess the strengths and weaknesses of the product and may subsequently support and promote or criticize the product. This activity involves actively reviewing or recommending the product (e.g., through word-of-mouth or social media) or simply talking about or broadcasting their purchase (e.g., "pins", "check-ins", "bought by", status updates, blog posts, tweets, etc.). Consumers may also emphasize the strengths of a product to confirm that they made the right decision. This assessment can affect their overall evaluation of the product, satisfaction with the purchase experience, and intention to repurchase.

2.2.2 Three Classes of Behavioral Biases

In this section, we introduce and briefly explain behavioral biases, which are widely covered in behavioral economics and marketing. We follow the framework of DellaVigna (2009) in classifying deviations (i.e., behavioral biases) of individual behavior from the standard economic model (Rabin 2002), which serves as a benchmark. The modern field of (micro) economics has already adopted many ideas from behavioral economics and currently has a far richer understanding of human behavior than the standard economic model suggests. Contemporary economists distinguish the following three classes of deviations from this model (DellaVigna 2009): nonstandard preferences, nonstandard beliefs, and nonstandard decision-making[5]. We follow this classification due to the following advantages. First, these classes are theoretically substantiated and widely used in the field of economics; however, these classes are also related to marketing and consumer psychology. Second, using the three classes, we can categorize a large set of individual biases based on economic theory and facilitate the uncovering of relationships among biases (i.e., aggregating insights). Third, using this framework is helpful because the standard economic model provides a well-defined benchmark.

2.2.2.1 Nonstandard Preferences

The first class of behavioral biases, nonstandard preferences, includes the following deviations from the standard economic model regarding the utility function: time-inconsistent preferences, reference-dependent utility, and social preferences. Regarding time-inconsistent preferences, empirical evidence suggests that individuals can have a "present bias" or "declining impatience", which is consistent with (quasi)-hyperbolic discounting (Laibson 1997; Loewenstein and Prelec 1992), that can capture consumers' problems of self-control. For example, a person signs up for a gym membership to force their future self to exercise. As the future approaches, the person must decide whether to exercise, and the future utility is discounted more steeply. Thus, the person tends to procrastinate and postpone exercising (DellaVigna and Malmendier 2006). Alternative theories, e.g., temporal construal level theory, can also help explain such behavior (Trope and Liberman 2000).

[5]The Appendix summarizes examples of each bias dimension from seminal papers, including a verbal definition and an illustration, in three tables (one per class of biases).

Furthermore, by assuming reference-dependent utility, loss aversion, and a nonlinear probability weighting function, prospect theory (Kahneman and Tversky 1979) addresses several issues supported by empirical evidence, such as that individuals 1) focus on relative versus absolute trade-offs and think in terms of gains and losses rather than overall wealth, 2) are more sensitive to losses than gains, and 3) over/under weigh small/large probabilities. Finally, vast empirical evidence suggests that people have social preferences and are not purely self-interested but are also concerned with social welfare and fairness, e.g., in ultimatum or dictator games (Camerer and Thaler 1995), or engage in charitable giving (DellaVigna et al. 2012).

2.2.2.2 Nonstandard Beliefs

The second class of deviations considered are nonstandard beliefs, which emerge in the presence of uncertain factors in decision-making. Under uncertainty, decision-makers must form beliefs regarding potential outcomes or "states of the world". The standard economic model predicts that, on average, people correctly evaluate the distribution of these states and update their beliefs using Bayes' rule for incoming information. However, empirical evidence suggests that consumers often form systematically incorrect beliefs and do not act as Bayesian information processors (DellaVigna 2009; Rabin 2002). Three main dimensions related to this context can be distinguished.

First, belief-based biases comprise overconfidence, which involves overestimating one's actual ability, performance, level of control, or chance of success; considering one's abilities to be better-than-average (overplacement); or being too confident of one's knowledge, e.g., overprecision (see, e.g., Moore and Healy 2008). Similarly, individuals may be overly positive about the prospect of a desirable outcome that is unrelated to their abilities or knowledge (overoptimism). As a result, a wide range of irrational behavior may occur, such as clinging to one's beliefs despite contradictory evidence, disregarding other prospects and opportunities, or underestimating risks (Windschitl and Stuart 2015).

Second, consumers might be affected by projection bias, i.e., individuals project their current state into the future, such as when ordering food in a hungry state (Read and van Leeuwen 1998) or ordering winter clothing on a cold day (Conlin et al. 2007). Third, the misconception that small random samples are as representative as large samples, which is known as the law of small numbers (Tversky and Kahneman 1971), might lead to false generalizations as people tend to ignore base-rate frequency (prior probability) and sample size when making inferences (Tversky and Kahneman 1974). Examples of the law of small numbers include the "gambler's fallacy" (Tversky 1974) and the related "hot hand fallacy" (Gilovich et al. 1985), which describe individuals' beliefs that respective negative or positive correlations exist in random processes.

2.2.2.3 Nonstandard Decision-Making

This class of deviations addresses observations of non-utility-maximizing behavior due to violations of the following assumptions: individuals are full and perfect information processors, who consider the incentives of information sources and make context-invariant choices; moreover, they are emotionless and deliberate.

The notion that choices are constructed (Bettman et al. 1998) and that the particular choice architecture (framing/context) affects the choices people make is generally accepted (Simonson 2008). For example, framing effects may emerge due to the reference-dependent utility function, which render some characteristics more salient or implicitly manipulate goals (see Levin et al. 1998). This pattern is also observed in an intertemporal choice context, such as "temporal frames" (Loewenstein 1988), which describes the same option (with the same time interval) as a delayed or expedited decision and can lead to different discount rates. Moreover, choices might be affected by context effects that emerge due to a choice set composition. In particular, a product may attract a larger share in settings in which it is a middle rather than an extreme option, which is referred to as the compromise effect. Relatedly, a locally inferior product can be introduced, resulting in the so-called attraction effect. Tversky (1972) further distinguishes the similarity effect, which implies that an alternative loses choice share relative to a more similar alternative.

Furthermore, the premise of individuals' limited cognitive abilities and limited attention has been addressed since Simon (1955). People tend to pay more attention to salient factors or ignore some available information. Considerations of inattention have given rise to many alternative decision rules of utility maximization, including elimination-by-aspect (Tversky 1972), lexicographic rules (Tversky 1969), and satisficing (Simon 1959).

Subsequently, studies investigating persuasion effects have largely disputed the assumption that rational agents are aware of the incentives of information providers (e.g., firms or politicians) and that they consider them when making decisions. Moreover, individuals' attitudes and behaviors might be subjected to social pressure (DellaVigna et al. 2012) or social influence, i.e., pressure from their reference group (e.g., peers or family).

Finally, emotions are largely neglected by standard economic theory. However, emotions, including visceral influences, e.g., hunger or thirst (Loewenstein 1996), anticipatory emotions, e.g., anxiety or fear, and anticipated emotions, e.g., regret (Loewenstein et al. 2001), have been shown to drive consumer behavior.

2.2.3 Research Process

To identify relevant articles for our review, we employed the Scopus[6] database and searched for articles with titles, abstracts, and keywords related to particular terms[7] without restriction regarding the publication date in the following leading marketing journals: *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *Journal of Consumer Research*, *Management Science*, *Journal of the Academy of Marketing Science*, *International Journal of Research in Marketing*, *Journal of Retailing*, *Journal of Consumer Psychology*, *Journal of Service Research*, *Marketing Letters*, *Quantitative Marketing and Economics*, and *Journal of Interactive Marketing.* As keywords, we used the main dimensions of the three classes of behavioral biases as discussed in the previous subsection (e.g., time-inconsistent preferences, overconfidence, or limited attention).

We found 724 keyword/journal counts from 697 unique articles (our "seed list"). After closer examination, we only retained empirical papers, further excluded papers that used the keywords in a different context (e.g., persuasion), and extended our list by adding relevant papers if necessary. The Journal of Marketing Research, Marketing Science, and Management Science emerged as the main outlets of marketing research related to behavioral biases. Furthermore, some biases were found to receive only minimal attention (e.g., law of small numbers), whereas other topics appeared very popular in the field of marketing and were associated with a large body of literature (e.g., reference dependence and framing/context effects). The keyword search indicated that even though the number of marketing papers related to behavioral biases is substantial, inconsistencies in terminology, definitional ambiguities, and alternative conceptual frameworks that do not explicitly rely on economic theory complicate the process of identifying relevant papers and synthesizing their results. Therefore, we chose to use the following alternative approach: We begin our review with a unifying framework and then build a concise structure by organizing and discussing the classes of behavioral biases within the phases of consumer purchase decision-making. We identify papers from our cleaned and augmented list by a (qualitative) combination of citation counts, journal quality, recency, and relevance. Our goal is to provide instructive examples of all classes of biases from marketing research and to highlight important links, distinctive features, and differences related to the phases of consumer purchase decision-making. We emphasize the "first" connection of a bias and phase, i.e., we highlight where particular biases originate.

[6]https://www.scopus.com

[7]The rationale for searching the title, abstract, and keywords is that this information is accessible to everyone and not behind a paywall. This permissibility facilitates the replicability of the process.

2.3 Behavioral Biases in Consumer Purchase Decision-Making

In this section, we review particularly instructive papers from marketing research to illustrate how each of the three classes of behavioral biases can influence each of the four phases of consumer purchase decision-making. We dedicate a subsection to each of the phases, and each of these subsections follows the same structure. We organize the reviewed papers into tables that present the class of behavioral biases, the specific bias(es), the exact reference, the key activities in the phase that are affected by the bias(es), the marketing instrument, and a summary of the key findings. Based on these tables, we discuss general insights and specifics about each phase. Finally, we compare the individual phases of consumer purchase decision-making and the three classes of behavioral biases, and we discuss connections and differences across phases and classes.

2.3.1 Need Recognition Phase

In this section, we discuss how nonstandard preferences, beliefs, and decision-making affect consumers during the need recognition phase, as they recognize needs through internal or external signals. We summarize the key findings in Table 2.1 and discuss general insights and specifics subsequently.

The existing marketing literature focusing on behavioral biases during the need recognition phase is limited. We believe that one explanation for this observation is that "recognizing a need" is intangible and often difficult to measure. Nevertheless, the examples in the table above illustrate how behavioral biases in each of the three classes can affect consumers' awareness of a need, and more examples are conceivable. Across the three classes, consumer behavior can be biased during the need recognition phase and not only during the subsequent stages. Although an error may be realized only after a purchase, its cause could occur during the need recognition phase. For example, external cues (e.g., colors in the environment) might trigger a need that leads to distorted product evaluations (e.g., higher awareness of orange sodas) and, eventually, to decisions during the subsequent stages (Berger and Fitzsimon 2008). Additionally, because advertising aims to trigger consumer needs, behavioral biases related to advertising appear to be a prominent theme during the need recognition phase. For example, advertising often leads to consumers learning about new nutritional information. However, Andrews et al. (1998) show that consumers often misinterpret (i.e., overgeneralize) the common nutrient content claims in advertising. Thus, advertising plays an important role in consumers' recognition of problems or needs, but the behavioral biases of consumers may influence the effects of the advertised claims.

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
Nonstandard preferences	Time-inconsistent preferences	Goukens et al. (2007)	Recognizing a need through an internal signal (hunger) and external signal (visual food cues)	Product	The authors demonstrate that hunger and visual food cues increase consumers' variety seeking (study 1). They show that when the perceived value of a desired object (e.g., a sandwich) increases, the number of alternatives deemed to satisfy this desire also increases. Specifically, hunger increases the perceived value of food items and, as a result, the set of products under consideration (i.e., higher variety seeking).
	Social preferences	Stenstrom et al. (2018)	Recognizing a need through an internal signal (menstrual cycle)	Promotion	The authors find that women feel the need to act more prosocially during their luteal phase than during their follicular phase. The authors suggest that during the luteal phase, women are more susceptible to charitable donation requests and promotions regarding gift-giving.
Nonstandard beliefs	Over-generalization	Andrews et al. (1998)	Recognizing a need through an external signal (advertising)	Promotion	Advertising can induce consumers to form systematically biased beliefs. For example, in the context of nutritional labeling, advertising is often a significant first step for consumers to learn about new nutritional information. However, the authors show that consumers misinterpret (i.e., overgeneralize) the common nutrient content claims in advertising.
Nonstandard decision-making	Persuasion	Hui et al. (2013)	Recognizing a need through an external signal (advertising)	Promotion	Persuasive cues (e.g., advertising) and consumers' contexts crucially affect the initial phase of consumer purchase decision-making. The authors show that the manipulation of consumers' in-store travel distance through mobile coupons influences unplanned spending. However, rational agents are not expected to deviate from their planned purchase behavior regardless of the path they travel in a store.
	Persuasion, framing	Cox and Cox (2001)	Recognizing a need through an external signal (advertising)	Promotion	The authors analyze the persuasive effect of advertising for health prevention services (i.e., mammograms). Their results show that anecdotal messages have the following interaction effect with framing: loss-framed anecdotal advertisements have a higher perceived informational value and lead to a greater perceived likelihood of undergoing a mammogram after viewing the ad. However, this interaction effect is not present for advertisements with statistical information.
	Social pressure	Gardete (2015)	Recognizing a need through an external signal (peers)	Place	The author studies social effects in the in-flight marketplace. The results show that the purchase probability of a media item increases, on average, by 30% if a lateral neighbor (i.e., a neighbor next to the passenger in the same row) makes a purchase. Classical social influence theories cannot sufficiently explain these patterns. For example, the author finds cross-category effects, suggesting that a purchase by a consumer in one category might have a negative influence on a neighbor's purchase probability in a different category.

Table 2.1. Relevant articles and key findings in the need recognition phase

2.3.2 Pre-Purchase Phase

In this section, we present how nonstandard preferences, beliefs, and decision-making affect consumers during the pre-purchase phase as they search for and evaluate alternatives. We summarize the key findings in Table 2.2 and discuss general insights and specifics subsequently.

In contrast to the need recognition phase, we identified numerous marketing papers that document how behavioral biases affect consumers during the pre-purchase phase. Across the three classes of behavioral biases, these papers are concerned with consumers' perceptions, assessments, and formations of attitudes toward brands and product alternatives. Nonstandard preferences play a central role in the evaluation of alternatives, especially through reference points (e.g., price and quality expectations; see Gneezy et al. 2014) and social preferences (e.g., fairness concerns, see Campbell 1999 and Gershoff et al. 2012).

Belief-based biases are especially important during the pre-purchase phase because they affect consumers' evaluations and searches for alternatives. Regarding the evaluation of alternatives, consumers often have to make forecasts about future events and behaviors–for example, how often they will go to the gym, how many trips they will take using car sharing, or how often they will use a specific feature of a product (e.g., Acland and Levy 2015; Goodman and Irmak 2013; Lambrecht and Skiera 2006). Because these situations often involve uncertainty and, therefore, complexity for consumers, belief-based biases frequently lead to distorted outcomes (e.g., overpaying for products in the purchase phase). Regarding searches, consumers may overestimate their own private information relative to the additional information they could acquire through increased search efforts (see Brynjolfsson and Smith 2000 in Table 2.2 for an empirical observation that is consistent with this argument). As a result, they may not search enough and may potentially miss superior alternatives.

Nonstandard decision-making, particularly in the form of choice architecture (framing/context), influences both consumers' search behavior and their evaluation of alternatives (see Diehl 2005; Levin and Gaeth 1988; Morwitz et al. 1998; Yang et al. 2013).

We identify promotion and price as the key marketing instruments connecting the three classes of behavioral biases during the pre-purchase phase. For example, advertised prices can act as psychologically relevant reference points (nonstandard preferences), induce biased expectations regarding future price developments (nonstandard beliefs), and affect evaluations and search efforts depending on the format in which they are framed (nonstandard decision-making).

Class of biases	**Bias**	**Author (Year)**	**Key activity**	**Marketing instrument**	**Key findings**
Nonstandard preferences	Reference depen-dence	Kalyanaram and Winer (1995)	Evaluation of alternatives	Price	The authors document that reference prices have a consistent and significant impact on consumers' evaluation of alternatives. Consumers react differently to price increases and decreases relative to the reference price - they react more strongly to price increases. In addition to external reference points, internal reference points can influence consumers' judgments of alternatives. Empirical evidence suggests that previous prices play an important role in the reference price formation process.
		Gneezy et al. (2014)	Formation of expectations	Product, Price	High prices increase the expectations against which consumers compare their experience in the context of wine tasting and consumption. If the experience meets or exceeds this reference point, the traditional price-quality effect is observed. However, if the price is high and the quality is relatively low, the product falls short of the consumer's reference point, and the price-quality relationship is reversed.
		Brasel and Gips (2014)	Product comparison and evaluation	Product, Place	In contrast to touchpads and mice, touchscreens generate stronger psychological ownership, which increases the endowment effect and the willingness-to-accept (WTA) of selected products. Therefore, consumer preferences for alternatives may be systematically distorted due to the endowment effect caused by differences in the input device.
	Social preferences	Campbell (1999)	Price evaluation and perception	Price	Consumers' inferred motives for a price increase of toys and the relative profit to be made by a firm due to the increase both affect consumers' perceived price fairness. If participants conclude that a firm has a negative motive (e.g., increasing profits) for a price increase, the increase is perceived as less fair compared to the case in which the firm has a positive motive (e.g., donating additional profits to charity).
		Gershoff et al. (2012)	Product evaluation	Product	The authors show that in the context of consumer electronics, product versioning might address consumers' fairness concerns and can lead to unfavorable product evaluations and brand preferences. In particular, if consumers learn that the inferior product is produced by degrading a superior configuration, a norm violation occurs, which is considered unfair and unethical.
Nonstandard beliefs	Present bias, Projection bias	Acland and Levy (2015)	Usage estimation	Price	Consumers overpredict future gym attendance, which the authors attribute to consumers having a naïve present bias such that consumers fail to predict the impact of immediate gratification in the form of a price discount on gym attendance. The participants exhibited incorrect beliefs consistent with a projection bias as they expected their future preferences regarding gym attendance to remain stable.
	Over-confidence	Lambrecht and Skiera (2006)	Usage estimation	Price	Consumers may overestimate their ability to predict their future demand and precision. Here, consumers over-(under-) estimate their future usage and are subsequently more likely to choose the flat-rate (pay-per-use) tariff during the purchase phase, even if it is not the least costly internet tariff.
		Brynjolfsson and Smith (2000)	Price search	Price	The authors compare searches on competing e-commerce sites. On average, within one month, households visit only 1.2 book sites, 1.3 CD sites, and 1.8 travel sites, reflecting very low levels of search across all categories. A plausible explanation for the limited search is overconfidence. Consumers might overestimate the precision of their own information regarding prices, thus underestimating the differences that might exist across different e-commerce sites, between online and offline channels, or over time.

Table 2.2. Relevant articles and key findings in the pre-purchase phase

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
	Overoptimism	Goodman and Irmak (2013)	Usage estimation of product features	Product	Overoptimism may affect the adoption of a product as consumers can be too optimistic about the usefulness of new product features of electronic products. Failure in the proper estimation of the future usage of new product features can lead to situations in which many-feature products are preferred over few-feature products.
		Meyer et al. (2008)	Usage estimation of product features	Product	The authors provide experimental evidence showing that while respondents are willing to pay for new features of electronic products, the actual usage of these features after purchase is rather limited.
	Law of small numbers	Cox and Cox (1990)	Price perception regarding stores	Price	Consumers seem to generalize from a small sample of advertised prices to the overall store price image. The authors analyze the effect of different versions of retail ads with differing price and product representations on the perceived store's overall price level. They show that if the advertised prices are displayed as reductions from a previously higher price, consumers perceive the store to have overall lower prices.
Nonstandard decision-making	Framing	Diehl (2005)	Product search	Product	Online environments are often assumed to offer lower search costs and the advantages of screening and sorting products. However, the combination of ordering with lower search costs or more recommendations can lead to lower choice quality, which can manifest itself in terms of a lower average quality of considered options and more attention to mediocre than better options from the considered set.
		Morwitz et al. (1998)	Price evaluation and price perception	Price	Partitioned prices decrease consumers' recalled total costs and increase consumers' product demand compared to all-inclusive or combined prices (see experiment 2). However, consumers are unlikely to differ in their judgments depending on how the price is presented, because the total costs remain the same.
		Levin and Gaeth (1988)	Evaluation of product attributes	Product	Describing ground beef as "75% lean" compared to "25% fat" increases favorability in a consumer's evaluation, which is not expected under standard rational decision-making, because both descriptions report exactly the same information only differently.
		Yang et al. (2013)	Construction of WTP and WTA	Price	In contrast to the predictions of the standard economic model, the authors demonstrate that labels (e.g., lottery, raffle, coin flip, or gamble) associated with risk elicit much lower willingness-to-pay (WTP) regardless of the amount of uncertainty involved in the offer.

Table 2.2. Relevant articles and key findings in the pre-purchase phase (continued)

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
	Limited attention	Thomas and Morwitz (2005)	Price perception	Price	Experimental evidence shows that people perceive the difference between $2.99 and $4.00 to be much larger than the difference between $3.00 and $4.00, which can be attributed to the so-called left-digit bias.
		Meyvis and Janiszewski (2002)	Information search	Product	When consumers predict a product's key benefits, they encounter both diagnostic and irrelevant information. The authors show that irrelevant information systematically weakens consumers' beliefs about the product's benefits.
	Persuasion	Cowley (2006)	Brand evaluation	Promotion	The results indicate that although consumers can identify exaggerated claims in multiple service categories (e.g., bar, bistro, cruise ship tour) as less credible than factual claims, their brand evaluations are nevertheless inflated after their exposure to the exaggerated claims. According to the standard economic model, consumers should consider that information providers have an incentive to "oversell" their product and thus brand valuation should not be affected.
	Persuasion/ social pressure	Argo et al. (2008)	Product evaluation, browsing	Product	The authors analyze the influence of the touching of clothing by attractive consumers on other consumers. They show that male consumers prefer products that have been previously touched by attractive females. However, their product evaluations should not be influenced, because the quality and value do not change..
	Emotions	Meloy (2000)	Evaluation of product information	Product	The author provides evidence showing that consumers' search for and evaluation of information prior to a purchase decision at a restaurant can be distorted. The magnitude of this distortion can be influenced by positive affect (e.g., a good mood).

Table 2.2. Relevant articles and key findings in the pre-purchase phase (continued)

2.3.3 Purchase Phase

In this section, we discuss how nonstandard preferences, beliefs, and decision-making affect consumers during the purchase phase, including the choice of the product, the quantity, and the timing of the purchase. We summarize the key findings in Table 2.3 and discuss general insights and specifics subsequently.

Similar to the pre-purchase phase, we find a considerable number of marketing papers documenting the effects of behavioral biases on consumers during the purchase phase. Considering all three classes of behavioral biases, these papers address consumers' choices of brands, product types (e.g., "want" versus "should"), corresponding quantities, and purchase timing. In particular, nonstandard preferences play a paramount role and affect the whole spectrum of decisions (including timing) during this phase. They can be driven by time-inconsistent preferences due to the purchase-consumption time-delay and self-control issues (e.g., Milkman et al. 2009, Milkman et al. 2010), by reference dependence in the case of bundled options (core product plus a component related to risk, e.g., probabilistic promotions–see Kalra and Shi 2010–or warranties–see Jindal 2015), by social aspects of the pricing mechanism (e.g., Pay what you want (PWYW), see Christopher and Machado 2019; Schmidt et al. 2015), by offered promotions (e.g., charitable donations, see Dubé et al. 2017), or by product features (e.g., fair trade labels, see also the meta-analysis of Tully and Winer 2014).

Belief-based biases, such as overconfidence and overoptimism, play a role and affect activities during the purchase phase if products are coupled with promotions that involve some element of uncertainty (e.g., conditional rebates, see Ailawadi et al. 2014). Additionally, when purchasing products for future consumption, consumers must form (subjective) expectations about uncertain conditions (e.g., weather, see Buchheim and Kolaska 2016, but also Busse et al. 2012, Busse et al. 2015), which can lead to a projection bias. Finally, consumers' purchase decisions of "uncertain" products (e.g., financial products, see Johnson et al. 2005) may be prone to the gambler's or hot hand fallacy.

Nonstandard decision-making, especially choice architecture, plays a prominent role in the purchase phase. Choosing a product from a set of alternatives formed in the pre-purchase phase typically implies trading off on different product attributes (e.g., quality, brand, packaging, price, etc.). In such situations, consumers may be susceptible to context effects, resulting in choices that are not consistent with standard decision-making (e.g., Dhar et al. 2000; Dhar and Simonson 2003; Kivetz et al. 2004). The framing of information can further affect purchase decisions by activating different consumer goals (Lee et al. 2015; Levin et al. 1998). Consumers often pay limited attention to or ignore important product information available

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
Nonstandard preferences	Time-inconsistent preferences	Milkman et al. (2009); Milkman et al. (2010)	Product rental and ordering	Product	When choosing between relative “want” and “should” products, consumers may exhibit present bias, i.e., have time-inconsistent preferences depending on whether the purchase is intended for immediate or future consumption (e.g., when renting DVDs). Whereas “want” (e.g., action movies or ice cream) products are preferred for immediate consumption, preferences shift toward “should” products (e.g., documentaries or vegetables) when buying for future consumption.
		VanEpps et al. (2015)	Lunch order	Product	When consumers select meals in advance instead of at lunchtime, this results in healthier choices. The time delay between order and consumption helps consumers to impose self-control and lowers lunch calories.
		Wertenbroch (1998)	Quantity decision	Price	The author finds that consumers with a high preference for unhealthy snacks (relative “want” consumers) may forgo quantity discounts for potato chips and cookies to ration their consumption, i.e., per-unit savings from buying in bulks, and, therefore, exhibit less price-sensitive behavior.
		Kivetz and Simonson (2002)	Reward choice	Promotion	In the context of delayed rewards (e.g., sweepstakes), consumers may commit to indulging by choosing luxury rewards (e.g., luxury massage) over cash rewards, even though the cash rewards have a higher value.
		Vohs and Faber (2007)	Purchase	Price	The authors show how the depletion of resources governing self-control may lead to higher spending for consumer goods (e.g., gum, candy, coffee mugs) due to the inability to resist impulse buying temptations (i.e., consumers jump from the need recognition phase to the purchase phase).
		Dubé et al. (2014)	Purchase timing	Product	The authors propose an experimental design that enables the simultaneous identification of both utility and discounting functions. In the context of adoption decisions for consumer electronics (i.e., Blu-ray players), only a small share of consumers exhibit present bias, i.e., employ (quasi-)hyperbolic versus the standard economic models’ implied geometric discounting. However, the authors find large heterogeneity across consumers and relatively low discount factor values.
	Reference dependence	Jindal (2015)	Product and extended warranty choice	Product	In the context of extended warranties for appliances (e.g., washing machines), the observed high price premia for products with such insurance are mainly driven by the loss aversion experienced by consumers (with a reference-dependent utility function).
		Kalra and Shi (2010)	Purchase	Promotion	Reference dependence is an essential factor for determining the optimal reward structure of sweepstakes bundled with food products. The reward structure, which may induce brand switching (due to the sweepstakes), will depend not only on the risk aversion of consumers but also on whether the consumer has a high or low preference for a particular brand.
		Kivetz (2003)	Reward choice	Promotion	Reference dependence plays a crucial role in determining rewards in the context of loyalty programs. In particular, the effort required of consumers for gaining rewards (e.g., frequent flyer miles) shifts the reference point such that consumers prefer sure-small rewards to larger risky rewards.

Table 2.3. Relevant articles and key findings in the purchase phase

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
	Social preferences	Schmidt et al. (2015)	Purchase and voluntary payments	Price	Social preferences, such as altruism and inequity aversion, along with strategic considerations, such as keeping the seller in the market, are the leading explanations of consumers' decisions to pay a positive amount to PWYW sellers.
		Jung et al. (2017)	Voluntary payments	Price	Field evidence in a retailing context shows that the presence of charitable donations as a nonprice promotion increases the amount consumers pay to PWYW sellers. However, consistent with an "impure altruism" account, consumers seem to be insensitive to the share of their payment that is donated to charity.
		Dubé et al. (2017)	Coupon redemption	Promotion	Charitable donations as a promotion also work in non-PWYW contexts and increase redemption rates when used as a direct marketing tool (SMS coupons) for movie tickets. However, donations do not work well together with deep price discounts because consumers update their beliefs about themselves, and deep discounts crowd out the self-inference of altruism.
		Hainmueller et al. (2015)	Purchase	Product, Price	Social preferences may be leveraged through product features, such as fair trade labels for consumer goods. The authors provide evidence from a large-scale field experiment in which coffee sales increased by approximately 8% when the product carried a fair trade label.
Nonstandard beliefs	Overconfidence	Soman (1998)	Purchase	Promotion	Overconfidence can lead consumers to underestimate the amount of effort required to use delayed promotions (such as mail-in rebates) for clothing (e.g., ski attire), which can lead to failure to redeem the rebate, also known as redemption "slippage."
	Overoptimism	Goldsmith and Amir (2010)	Product choice	Promotion	Experimental and field evidence shows that uncertain sweepstakes (i.e., it is not clear whether the consumer will win a higher or lower quality prize) coupled with a food product are as effective (i.e., lead to similar purchase likelihoods) as certain sweepstakes that offer only the higher-quality prize. In the case of uncertain sweepstakes, consumers are overoptimistic and act as if they expect to win the higher quality prize.
		Ailawadi et al. (2014)	Product choice	Promotion	Consumers are overoptimistic about receiving a "conditional rebate" for consumer electronics and appliances, which are conditional on the occurrence of some uncertain external event (e.g., a specific team wins a major sports event).
	Projection bias	Buchheim and Kolaska (2016)	Purchase	Place	Projection bias is a leading explanation of a 40-50% increase in advanced online ticket sales for a movie at an outdoor cinema due to sunny weather on the day of purchase even though the weather on the day of purchase is a bad predictor of future weather conditions.
	Law of small numbers	Johnson and Tellis (2005)	Buying and selling	Product	Experimental evidence demonstrates that in the context of financial products, most consumers tend to "buy a winner" (i.e., hot hand fallacy), whereas only a small share buys "a loser" (i.e., gambler's fallacy) in hope of a reversing trend.

Table 2.3. Relevant articles and key findings in the purchase phase (continued)

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
		Johnson and Tellis (2005)	Buying and selling	Product	In the context of financial products, the hot hand fallacy seems to increase with the length of the trend. However, after a certain threshold, the preference for buying the "winner" decreases for very long trends.
		Narayanan and Manchanda (2012)	Gambling	Product	Using observational data at the individual level about gambling behavior, the authors find that prior wins (losses) have a negative (positive) effect on current betting behavior even though past results of a random event should not influence the current behavior of a rational consumer.
Nonstandard decision-making	Choice architecture	Kivetz et al. (2004)	Product choice	Product	The authors present empirical evidence supporting the presence of a compromise effect in multiple categories of consumer electronics in which consumers prefer a third middle option with a trade-off in two dimensions (e.g., speed and memory for PCs and power and price for speakers).
		Rooderkerk et al. (2011)	Product choice	Product	The authors consider all three context effects in digital camera choice simultaneously and show that they co-occur even after controlling for taste heterogeneity. Models accounting for context-dependent and context-independent preferences simultaneously outperform the standard economic model.
	Framing	Lee et al. (2015)	Product choice	Product	In multiple product domains (e.g., flights, software, vacation, etc.), saliency of product attributes affects the trade-off between money- and time-related dimensions. Money considerations activate analytical processing, whereas time considerations lead to affective processing. Interestingly, the former leads to a larger number of violations of transitivity in choice. Additionally, framing of price information, such that its interpretation is constrained, can mitigate the preference inconsistency.
		Cheema and Patrick (2008)	Coupon redemption and purchase	Promotion	The framing of promotional information can influence purchase decisions at a coffee shop. Only manipulating the wording (but not the length) of the time window in which coupons can be redeemed affects the redemption and, therefore, purchase rates.
	Limited attention	Dickson and Sawyer (1990)	Product choice	Price	The authors conducted a field study at supermarkets, and even though price is an important driver of consumer behavior, only half of the consumers reported to have checked prices and were able to provide an accurate price estimate of their selected products.
		Balasubramanian and Cole (2002)	Product choice	Product	The authors find poor results in terms of recall and accuracy for nutritional information on food products. Additionally, consumers who consult nutrition information pay more attention to negative (e.g., calories) rather than positive (e.g., protein) nutrient information.
		Mohr et al. (2012)	Product choice	Product	Educating consumers about how to interpret the nutritional information of food products, including serving sizes, which are otherwise frequently ignored, affects product choice, nudging consumers toward healthier options.
	Emotions	Ding et al. (2005)	Bidding	Price	In a Priceline-like reverse auction, the authors find that the excitement of winning and the frustration of losing affect bidding decisions for vacation packages, which is inconsistent with the standard economic model.

Table 2.3. Relevant articles and key findings in the purchase phase (continued)

during their purchase, including prices (e.g., Dickson and Sawyer 1990) and nutrition labels (Mohr et al. 2012).

We identify biases related to product and price as the main area of research in the purchase phase. In particular, time-inconsistent preferences affect many key activities in the purchase phase. Moreover, the coupling of products (and their features) with pricing schemes, promotional activities (e.g., sweepstakes and lotteries), other products, or warranties and insurance creates purchase situations in which behavioral biases are likely to play a role.

2.3.4 Post-Purchase Phase

In this section, we discuss how nonstandard preferences, beliefs, and decision-making affect consumers during the post-purchase phase. Notably, we illustrate how each of the three classes of behavioral biases may influence the post-purchase activities of consumers, such as returning the product or actively recommending the item via word-of-mouth. Table 2.4 summarizes the key findings. General insights and specifics are discussed subsequently.

The selected articles covering behavioral biases during the post-purchase phase reveal that the body of literature is not as rich as for the pre-purchase and purchase phases. Although one reason for fewer papers related to the need recognition phase is the difficulty in measuring the dependent variable, this rationale does not necessarily apply to the post-purchase activities, such as word-of-mouth or repurchase intention. However, most studies include these measures as independent variables and analyze their impact on purchases. Nevertheless, as we outlined, all classes of biases can affect the post-purchase activities of consumers. Specifically, nonstandard preferences play a role in remote purchase environments through reference dependence and the endowment effect and may affect product returns and subsequent purchase decisions, e.g., of extended warranties (see, e.g., Wood 2001). In addition, the endowment effect is also relevant considering the separate decision for an extended warranty after the purchase decision as a post-purchase activity (Chark and Muthukrishnan 2013). Nonstandard beliefs also affect consumers' post-purchase activities, such as those driven by customers underestimating their ability to provide effective word-of-mouth (e.g., Hagenbuch et al. 2008). Nonstandard decision-making affects post-purchase activities through emotions (e.g., Phillips and Baumgartner 2002), including word-of-mouth, brand switching, and satisfaction (Romani et al. 2012). A multitude of the biases identified in the post-purchase phase is related to the marketing instrument product.

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
Nonstandard preferences	Reference depen-dence	Wood (2001)	Keep and return decision	Place	The endowment effect influences consumers' decisions in remote purchase environments (e.g., catalog sales or online retailing). More lenient return policies (full refund versus no refund for shipping costs) not only positively affect ordering decisions but also lead to more positive quality ratings after a physical examination of the product (i.e., post-purchase). Furthermore, keep/return deliberation times (i.e., decision conflict) and return rates are not significantly influenced, and hence, the endowment effect might mitigate the potential negative consequences of lenient return policies.
		Chark and Muthukrishnan (2013)	WTP for extended warranties after purchase	Product	Touching a smartphone or notebook after delivery increases the WTP for extended warranties. Thus, the endowment effect is relevant considering the separate decision for an extended warranty after the purchase decision as a post-purchase activity.
		Jindal (2015)	WTP for extended warranties after purchase	Product	Loss aversion increases the WTP for extended warranties if sold separately after the purchase of a washing machine. Compared to the bundled case, loss aversion (and its heterogeneity) is even higher, and therefore, the price premia are also higher when consumers choose the extended warranty after the product purchase.
Nonstandard beliefs	Over-estimation	Hagenbuch et al. (2008)	WOM	Product	The authors analyze why even satisfied and devoted consumers of an accounting service seldom or never offer product recommendations in the post-purchase phase and find that in addition to attitudes toward referral-giving, related beliefs are relevant. Even though consumers have full control over giving referrals or spreading word-of-mouth, they refrain from such activities because they underestimate their skills or resources (i.e., perceived lack of control) to perform these tasks successfully.
		Berger and Iyengar (2013)	WOM	Product	Communication channels affect consumers' word-of-mouth content. In the case of written (e.g., online, e-mail, and text message) and oral (e.g., face-to-face and phone) communication, consumers tend to "talk" more about interesting products and brands due to self-enhancement motives. Related to nonstandard beliefs, consumers might engage in written word-of-mouth too often if they overestimate their reach.

Table 2.4. Relevant articles and key findings in the post-purchase phase

Class of biases	Bias	Author (Year)	Key activity	Marketing instrument	Key findings
Nonstandard decision-making	Emotions	Phillips and Baumgartner (2002)	Judgment of satisfaction	Product	Both positive and negative emotions have been shown to drive satisfaction beyond the standard expectation-disconfirmation effects for food products.
		Zeelenberg and Pieters (1999)	Complaint and switching behavior, WOM	Product	Different negative emotions can trigger different post-purchase responses in addition to dissatisfaction in multiple service categories (e.g., transportation, repair and utility services). In particular, the authors find that feelings of disappointment are more associated with negative word-of-mouth, whereas feelings of regret may result in brand switching.
		Romani et al. (2012)	Complaint and switching behavior, WOM	Product	The authors developed a scale for six negative brand-emotions as well as support and further extend findings of Zeelenberg and Pieters (1999). In addition to disappointment, they find that anger may also lead to negative word-of-mouth (e.g., saying negative things about a brand and discouraging others from buying the brand), while feelings of regret and worry may result in brand switching as a post-purchase activity in multiple product domains. Additionally, feelings of sadness and embarrassment prompt consumers to stay passive in their post-purchase responses.
		Louro et al. (2005)	Repurchase intentions	Price	Even positive emotions can reduce repurchase intentions for consumer electronics and clothing products. If price discounts are framed as not losing money (i.e., the prevention of a loss), consumers with high pride have a decreased repurchase intention because they associate the following nonpromotion purchase with a loss.

Table 2.4. Relevant articles and key findings in the post-purchase phase (continued)

2.3.5 Insights Across Phases and Classes of Behavioral Biases

By comparing the individual phases and classes of behavioral biases, we identify nonobvious connections and derive additional insights. In this section, we discuss the connections and differences across phases and classes of biases. We also present insights into the interdependencies among the multiple phases, repeat purchases, marketing instruments and product type, and discuss potential moderators.

2.3.5.1 Connections and Differences Across Phases and Classes of Biases

Notably, a rich literature covers behavioral biases during the pre-purchase and purchase phases, whereas marketing literature dedicated to behavioral biases during the need recognition and post-purchase phases is rather scarce. Moreover, the three classes of behavioral biases appear to be documented to different extents across the phases. For example, nonstandard decision-making is widely relevant across phases, whereas nonstandard preferences and nonstandard beliefs are particularly prominent during the pre-purchase and purchase phases, as shown in Figure 2.1.

Because the four phases comprise different key consumer activities (as outlined in section 2.2), it is evident that the three classes of behavioral biases have different levels of importance across the phases. For example, nonstandard preferences are particularly important during the pre-purchase and purchase phases since consumers' preferences are relevant for the activities performed during these two phases. During both evaluation of and search for alternatives and the quantity and timing of the actual purchase, consumers are heavily influenced by time-inconsistent preferences (e.g., due to the time lag between the purchase and consumption), preferences for other people (e.g., fairness concerns), and various reference points (e.g., reference prices).

Nonstandard beliefs play a role when consumers must make predictions about their future behavior, which usually involves uncertainty, which again mostly concerns activities performed during the pre-purchase and purchase phases. During the pre-purchase phase, consumers often form expectations about their future usage of a product (e.g., frequency or extent of feature usage). During the purchase phase, consumers form expectations about additional aspects of the purchase that are only realized after the purchase has been made (e.g., uncertain promotions). However, we argue that relative to the other phases, most activities in the pre-purchase phase require consumers to make predictions and are therefore especially prone to belief-based biases. However, belief-based biases can also influence activities during the need recognition and post-purchase phases. For example, during the need recognition phase, consumers may overgeneralize advertising claims. During the post-purchase phase, consumers may be overconfident about the impact on the seller of writing a product review.

Nonstandard decision-making plays an important role in all phases of consumer purchase decision-making. Framing and choice architecture appear to be especially prominent during the pre-purchase and purchase phases, during which consumers evaluate and choose from multiple alternatives. How alternatives are described and presented can influence consumers' WTP, search behavior, and eventually, product choice. Nonstandard decision-making also influences consumers during the need recognition phase. It may seem odd to encounter the term "decision-making" during the need recognition phase. However, a consumer's social environment also often plays an essential role in influencing and determining perceived needs. The class of nonstandard decision-making includes biases involving external cues that influence consumers, such as persuasion or social pressure. For example, persuasion through advertising can play an important role in triggering a need during the need recognition phase. The aforementioned prevalent biases in the class of nonstandard decision-making, such as framing, are seemingly less relevant in the post-purchase phase. However, emotions can be of relevance in this phase. Dissatisfied customers often experience negative emotions after a purchase, such as disappointment and regret, that influence their post-purchase activities, such as word-of-mouth or return behavior.

Another explanation for why the three classes of behavioral biases appear to be documented to different extents across the phases involves measurement and issues related to identification. Especially during the need recognition phase, biases seem more difficult to detect. This is related to the fact that needs are "intangible" and often difficult to articulate. Moreover, identifying biases can be methodologically challenging. For example, to elicit subjective beliefs, researchers may rely on unincentivized questionnaires. The resulting problem is that such unincentivized belief measures may be biased due to socially desirable and self-serving answering behavior (Grewening et al. 2019).

2.3.5.2 Interdependencies Among Multiple Phases and Repeat Purchases

First, we observe that some biases span multiple phases. For example, behavioral biases may originate during the pre-purchase phase but also have an effect on behavior during the purchase and post-purchase phases. For example, Goodman and Irmak (2013) show that consumers prefer many-feature products and pay a higher price for such products because they overestimate their feature usage rate or fail to estimate their usage altogether (during the pre-purchase and purchase phases). This also has an effect on the post-purchase phase, as estimating the usage prior to purchase induces greater product satisfaction and a greater likelihood of recommending the product.

Second, consumers are assumed to transition through the four phases multiple times in the case of repeat purchases (e.g., consumables), allowing behavioral biases to play different roles as consumers gain experience. For example, consumers switch telephone plans by adopting the optimal plan as they gain experience (Miravete 2003). Similarly, credit card users pay fewer fees as they gain more experience with their card (Agarwal et al. 2013). However, experience does not always attenuate biases. For example, cognitive dissonance theory explains why overconfident beliefs may persist over time. Because consumers aim to avoid the stress caused by information that challenges their beliefs, they may attempt to avoid such belief-changing information (Malmendier and Taylor 2015).

2.3.5.3 Marketing Instruments and Product Type

Whereas behavioral biases pertaining to product are well documented across all phases, behavioral biases concerning place are rather scarce. Notably, most studies focusing on price document behavioral biases related to nonstandard preferences during the pre-purchase and purchase phases, which is sensible as prices constitute numerical information that frequently serves as an important reference point during the pre-purchase and purchase phases. For example, even irrelevant price information can influence consumers through anchoring and adjustment (Adaval and Wyer 2011). The marketing instrument promotion occurs in all phases and classes of biases. Persuasion and framing in advertisements seem to be particularly common research topics in this regard.

Depending on the product type (e.g., consumables or durables), the individual phases may see different weights in purchase decision-making. For example, consumers might be more likely to skip phases and jump directly to the purchase (i.e., impulse buying) in the case of consumables. In the context of durable goods purchases, it is likely that the evaluation phase will be relatively more extensive and thus will lead to consumers' engagement in greater amounts of search and deliberation.

2.3.5.4 Moderators

The moderators of behavioral biases have been widely neglected in the marketing literature. However, our review reveals at least the following two important moderators: technology and time. We present several examples in which technology moderates the effects of biases. First, Brasel and Gips (2014) show that touchscreens (versus mice) create stronger psychological ownership, which increases the endowment effect. Second, Hui et al. (2013) find that mobile coupons can alter consumers' in-store travel paths, which can lead to increased unplanned spending.

Third, consumers who do not understand how technology-enabled decision aids operate may engage in harmful behavior. Diehl (2005) shows that consumers who do not understand that they are in an ordered search environment may be tempted to engage in more searching, which can result in choosing lower-quality options.

Time can moderate behavioral biases in various forms, e.g., as time lag (e.g., between purchase and consumption) and time pressure (e.g., through deadlines). The time lag between evaluation and purchase or purchase and consumption can either cause biases into existence or increase or attenuate existing biases. For example, time-inconsistent preferences or belief-based biases (e.g., projection bias) only emerge if a time lag exists. However, the time lag's magnitude can moderate the biases. For example, Milkman et al. (2010) show that a larger time lag influences consumers' self-control. The larger the time lag, the less "want" products (relative to "should" products) consumers order. In a similar context, VanEpps et al. 2015 demonstrate that advance meal selection (thus a larger time lag) can promote healthier eating decisions. In addition, it is conceivable that time pressure can moderate biases in various phases of consumer purchase decision-making. Decisions under uncertainty (e.g., auctions) often involve time pressure. Research investigating risky decisions under time pressure has found that time pressure can lead to more risk aversion for losses (Kocher et al. 2013). For mixed prospects, however, time pressure simultaneously increases loss aversion and gain seeking.

2.4 Managerial Implications and Avenues for Future Research

As previously shown, marketing scholars have made substantial contributions to the growing body of literature on behavioral biases. Numerous biases can affect consumer behavior across all phases of purchase decision-making. Understanding these behavioral effects offers marketing practitioners opportunities by which to adapt their marketing strategy accordingly. We summarize key points and specific implications in Table 2.5, along with a detailed discussion. Additionally, the insight generated from our review provides important avenues for future research, which we discuss and additionally outline in Table 2.6.

2.4.1 Managerial Implications

2.4.1.1 Behavioral Biases in Digital and Digitally Enhanced Environments

Current marketing practices already exploit some behavioral biases. For example, firms offer uncertain sweepstakes, which utilize the potential overoptimism of consumers (Goldsmith and Amir 2010), or offer partitioned prices, which may increase demand through framing effects (Morwitz et al. 1998). However, as previously explained, technology may moderate behavioral biases, and new trends

Topic	Key points	Related literature	Practical implications
Behavioral biases in digital and digitally enhanced environments	New digital technologies and resulting functionalities (e.g., touch on mobile devices) can lead to the endowment effect when shopping online.	Brasel and Gips (2014)	Retailers may design websites such that they foster the use of touch on mobile devices to capitalize on the endowment effect.
	Augmented reality in online channels can attenuate overconfidence and enhance projection bias.	Yaoyuneyong et al. (2014)	Retailers may consider adopting augmented reality in online channels. Consumers potentially will make better decisions
	Lower uncertainty in the pre-purchase phase may reduce the effects of negative emotions in the post-purchase phase.	Romani et al. (2012)	due to lower uncertainty (e.g., in the sizing of clothing), and retailers may benefit from more satisfied consumers and less negative word-of-mouth in the long-run.
	Shorter delivery times lead to (online) impulse buying and increase the preference for “want” products.	Milkman et al. (2010)	When reducing delivery times retailers should consider adjusting their assortment and inventory (i.e., stock more “want” products). Additionally, they could help consumers make better decisions offering options for a better planning of recurring purchases.
Big data and data analytics	Big data enables precise measurement of consumer states. Using persuasive cues and targeting consumers at the right time and place can induce unplanned spending.	Vohs and Faber (2007); Hui et al. (2013)	Location-based advertising can be used to target people stuck in traffic or when they are resource-depleted. RFID chips and Bluetooth beacons can be used to increase the travel distance in-store.
	Adaptive websites enable firms to capitalize on framing effects and choice architecture.	Hauser et al. (2009)	Firms may use past clicks and other information to dynamically adjust their websites for each consumer and help to make decisions easier, more practical, and efficient.
		André et al. (2018)	When using data analytics, automation, and targeting, firms need to be careful that consumers do not feel like they are losing autonomy over their own decisions.

Table 2.5. Overview of managerial implications

Topic	**Key points**	**Related literature**	**Practical implications**
Behavioral biases and marketing instruments	Versioning as a product line strategy can lead to adverse effects due to social preferences.	Gershoff et al. (2012)	To mitigate negative effects, firms should communicate that versioning is a common practice in the industry.
	It is essential to consider framing effects when advertising price discounts.	Krishna et al. (2002)	Firms should use price discounts in terms of percentages rather than absolute amounts.
	Uncertain promotions can have positive effects in the purchase phase due to belief-based biases.	Goldsmith and Amir (2010)	Retailers can benefit from overoptimistic consumers by using sweepstakes as nonprice promotions.
	The channel for selling durables (online vs offline) affects the WTP for extended warranties because of the endowment effect.	Chark and Muthukrishnan (2013)	Retailers should use price differentiation for extended warranties depending on whether a customer buys online or offline, i.e., set higher prices in the case of offline purchases.
Negative consequences of exploiting behavioral biases	Taking advantage of behavioral biases for profit-maximizing purposes may backfire due to consumers' fairness concerns (social preferences).	Thaler (2018); Gershoff et al. (2012)	Firms should set internal boundaries and a code of conduct for how they balance leveraging behavioral biases and protecting their customers' best interests.

Table 2.5. Overview of managerial implications (continued)

and developments in marketing in the digital age may further affect consumer behavior and their reactions to biases. In particular, digital technologies and environments may create situations in which certain biases appear or influence the magnitude of already occurring biases.

Augmented reality as a new technology affects consumers' online service experiences (see e.g., Hilken et al. 2017) and may, similar to the use of touch on mobile devices (Brasel and Gips 2014), induce the endowment effect in online shopping by helping consumers imagine items such as furniture in their actual apartments (Javornik 2016) or vacations to distant locations (Dadwal and Hassan 2015). Moreover, as outlined in Table 2.5, augmented reality may reduce overconfidence and enhance projection bias (e.g., booking a vacation to a warm place when the weather is bad). As a result, augmented reality may create interactions among multiple biases (i.e., endowment effect and overconfidence or projection bias) during the pre-purchase phase. Furthermore, because biases can span multiple stages or even interact across stages, the reduction in belief-based biases could help firms with post-purchase activities, such as negative word-of-mouth triggered by emotions (Romani et al. 2012).

Yadav and Pavlou (2014), highlight the increasing interaction between consumers and new technologies, and in some cases, this interaction has the potential to affect the magnitude of time-inconsistent preferences during the purchase phase. For example, better (i.e., faster) delivery services for products, e.g., "Prime Now" by Amazon offering delivery within the next (couple of) hour(s), allows consumers the opportunity to immediately satisfy their needs, which is very likely to induce consumers to engage in more (online) impulse buying as well as to increase the consumption of "want" products driven by time-inconsistent preferences. Shorter delivery times, therefore, might affect the firm's inventory and assortment decisions. However, online channels might still lead to fewer purchases of unhealthy products than offline channels (Huyghe et al. 2017), and modern planning apps (e.g., grocery pal) that help people organize and make recurrent decisions, such as grocery shopping, might also reduce impulse buying. Firms can thus both exploit and help consumers avoid biases.

Digital markets, media platforms, and the shift from desktop to mobile device usage have changed the marketing landscape. These changes offer new ways (i.e., new contexts) to reach, inform, engage, and provide service to consumers in all stages of their decision-making, possibly moderating behavioral biases. For example, mobile devices provide more opportunities to search for information. However, simultaneously, the smaller screens may lead to higher search costs and reduced search activity. In such situations, salient information, e.g., top products based on ranking lists (e.g., provided by the firm), may be more persuasive due to impaired searching (Ghose et al. 2013). This may be due to framing, as in Diehl

(2005), and implies relatively weaker competition if consumers are reached via mobile devices. Therefore, firms need to adjust their pricing and recommendation strategies accordingly.

Finally, new communication and sales channels are emerging, and consumer behavior via these channels needs to be assessed. For example, autonomous driving enables new activities that were not possible before to be performed inside a car while traveling. More specifically, cars provide a new environment in which to show ads and stimulate searching during the pre-purchase phase, induce impulse buying, and enhance framing effects through new contexts. For firms, this implies new opportunities for real-time targeting.

2.4.1.2 Big Data and Data Analytics

In the digital age, firms currently have access to more and better data regarding the entire customer journey (Wedel and Kannan 2016). These data are useful not only for predicting clicks, searches, and purchase behavior but also for measuring behavior related to the need recognition phase (e.g., interaction with peers in social networks) as well as the post-purchase phase (e.g., electronic word-of-mouth) and provide a "window into consumers' psyche" (Matz and Netzer 2017). Moreover, automated textual analysis enables generating relevant marketing insights (Berger et al. 2019). Understanding the psychological aspects of how consumers behave in digital markets is crucial for firms (Lamberton and Stephen 2016).

Consumers make more impulse buying decisions when they are resource-depleted (Vohs and Faber 2007). Thus, firms can target such consumers to increase unplanned spending given that this consumer state is measurable (e.g., using location-based advertising). Furthermore, mobile coupons can be used as persuasive cues to increase the travel distance, which might lead to more impulse buying (Hui et al. 2013).

In general, individual-level data and online markets make targeting consumers easier (Wedel and Kannan 2016). Reference-price effects related to personalized pricing (e.g., Zhang and Krishnamurthi 2004) are particularly relevant during the pre-purchase and purchase phases. Adaptive websites (Hauser et al. 2009) are an example of how firms utilize new individualized digital interfaces with an opportunity for framing and choice architecture by dynamically adjusting their websites to each consumer based on past clicks and other information. However, managers should be aware that this practice can also lead to negative consequences if consumers feel that they are losing autonomy over their own decisions (André et al. 2018). Finally, although it is challenging to combine and integrate data from different sources (Lambrecht and Tucker 2015), tracking consumers across channels (i.e., online and offline) could provide managers with a more complete picture of consumers.

2.4.1.3 Behavioral Biases and Marketing Instruments

Managers have various marketing instruments at their disposal to affect consumers and exploit behavioral biases.

Related to product, firms should be careful when using versioning as a product line strategy, because versioning may lead to negative attitudes of consumers during the pre-purchase phase due to social preferences. However, firms may attenuate the issue by informing consumers that versioning is a common practice, making products more dissimilar in superficial characteristics (e.g., color), or using different distribution channels (Gershoff et al. 2012). Context effects that may play a role during the purchase phase are also important to consider when designing a product line. For instance, considering the compromise effect (e.g., Kivetz et al. 2004), firms may introduce a high-quality/high-price alternative or keep a low-quality/low-price alternative on the market to increase the share of the "middle" option. Other aspects of the product, including labels and packaging, may be framed to favorably influence consumers' evaluations of products (Levin and Gaeth 1988).

Price provides firms many opportunities to leverage biases, particularly during the pre-purchase and purchase phases. For instance, firms may affect consumers' perceived savings by framing price discounts in terms of percentages rather than in absolute amounts (Krishna et al. 2002). Specifically, presenting the discount depth as a comparison against the sale price increases the perception of the discount level and thus the purchase intention of consumers (Guha et al. 2018). However, firms should be wary of the possibility that advertised prices and frequent price discounts may decrease reference prices and lower the overall store price image. Retailers planning price promotions for "want" and "should" products should consider that consumers with time-inconsistent preferences may anticipate their self-control problems and, therefore, be less price-sensitive (Wertenbroch 1998). Furthermore, using partitioned prices or nine-endings may increase demand due to consumers' poorer recall of total costs (Morwitz et al. 1998) and limited attention to the leftmost digits (Thomas and Morwitz 2005).

Regarding promotion, firms may use anecdotal evidence in advertising messages (e.g., Cox and Cox 2001), mobile coupons, and visual in-store cues to capitalize on the persuasion bias (Hui et al. 2013). Consumer activities during the purchase phase can also be strongly affected by promotion, e.g., by deploying uncertain sweepstakes (Goldsmith and Amir 2010) or mail-in rebates (Soman 1998), which may affect consumers' decisions due to belief-based biases, such as overoptimism and overconfidence.

Place as an instrument is also relevant for managers, particularly in combination with other instruments. For example, in their online channel, firms may induce context effects (e.g., the compromise effect) influencing product choice during the purchase phase by presenting different configurations of products to offer a trade-off between features (e.g., quality and price) on the same page of their website. In the context of durable-goods purchases during the post-purchase phase, firms may increase consumers' WTP for extended warranties due to the endowment effect by offering warranties after delivery, i.e., after the consumers have received (and touched) the product (Chark and Muthukrishnan 2013). Furthermore, firms may capitalize on the endowment effect by offering lenient return policies in which consumers can return products at no additional cost (Wood 2001).

Finally, managers should be aware that potential interaction effects may exist between instruments. For example, according to Dubé et al. (2017)), deep price discounts may negatively interact with charitable donations as a promotional tool for exploiting social preferences.

2.4.1.4 Negative Consequences of Exploiting Behavioral Biases

Although firms may benefit from utilizing behavioral biases, such a strategy may backfire, and firms must be aware of the potential negative consequences. On the one hand, the understanding of behavioral biases can be used for doing good, i.e., to "nudge" people toward better choices related to their health, safety, and welfare (Sunstein 2015). For example, a food company could help consumers eat more healthfully by choosing specific alternatives, or a pharmaceutical company could help its patients take their medicine more consistently (Conick 2017). On the other hand, behavioral biases can be exploited for profit-maximizing purposes by firms at the expense of consumer welfare (Thaler 2018). For example, firms may exploit consumers' overconfidence with mail-in rebates and benefit from the redemption "slippage" discussed in section 2.3 (Soman 1998). This situation has recently been termed a "sludge" (Thaler 2018), and our review already showed the potential negative consequences on firms if consumers become aware of their practices. Gershoff et al. (2012) highlight that the social preferences (i.e., fairness concerns) of consumers may be affected. Furthermore, we contend that consumers might avoid a brand if they feel outsmarted and begin spreading negative word-of-mouth. Currently, information about pricing and general firm practices is more visible due to online environments, and this issue is becoming even more pronounced.

Additionally, regulators and consumer protection agencies are likely to intervene if firms are unwilling to commit to staying within reasonable boundaries. A better understanding of behavioral biases and using this knowledge to achieve win-win situations in which consumers' and firms' goals are consistent should be in firms' long-term interests.

2.4.2 Future Research

2.4.2.1 Phases of Consumer Purchase Decision-Making and Classes of Behavioral Biases

Across the four phases of consumer purchase decision-making, behavioral biases in the need recognition phase and the post-purchase phase have been studied less extensively. In these phases, we observe that nonstandard preferences and nonstandard beliefs have received less attention. We suggest that future research focus on these understudied combinations of phases of decision-making and classes of biases. For example, as outlined above, during the post-purchase phase, consumers may be overconfident about the impact of leaving a product review on the seller, and such topics warrant more extensive research.

We showed that interdependencies among the different phases also exist. For example, biases influencing purchase decisions may originate during the need recognition or post-purchase phases (e.g., in the case of repeat purchases). Moreover, repeat purchases allow behavioral biases to play different roles as consumers gain experience. For a complete and accurate understanding of biases within and across phases, we suggest that future research should focus on studying the biases at the phase where they originate and their influence on activities in subsequent phases. For instance, as Goukens et al. (2007) show, hunger and visual food cues can induce consumers to perceive more products as satisfying during the need recognition phase, resulting in stronger variety seeking. As a result, consumers may consider and evaluate a set of alternatives during the pre-purchase phase that they would not have considered otherwise, which ultimately affects their purchase decision as well as subsequent customer satisfaction and post-purchase activities.

Finally, moderators of behavioral biases have also received little attention in the marketing literature. We identified technology and time as relevant moderators, and future research could systematically explore other potential moderators. For example, behavioral biases may playout differently in individual vs. group decisions (e.g., household or firm decisions). Some empirical evidence suggests that behavioral biases persist in B2B markets involving firms' pricing (e.g., Bruno et al. 2012; Steiner et al. 2016), and due to time pressure and limited attention, managers often rely on heuristic decision rules (Guercini et al. 2015). It is, however, unclear whether biases affect group (e.g., firm) decisions at a lower magnitude due to potential learning and experience.

2.4.2.2 Marketing Instruments

Price, promotion, and product are the marketing instruments for which behavioral biases have been heavily studied in each phase of consumers' purchase decision-making. Certain topics in these research areas have even received so much attention

Research topics	Future research avenues	Relevant articles	Next steps
Phases of consumer purchase decision-making and classes of behavioral biases	Nonstandard preferences and nonstandard beliefs in the need recognition and post-purchase phase.	Hagenbuch et al. (2008); Berger and Iyengar (2013)	Study the effect of overconfidence on leaving a product review during the post-purchase phase.
	Interdependencies across phases.	Goukens et al. (2007)	Examine the effect of visual cues and hunger in the need recognition phase on the downstream effects in subsequent phases.
	Moderators of behavioral biases within and across phases.	Bruno et al. (2012); Steiner et al. (2016); Guercini et al. (2015)	Analyze moderators of behavioral biases beyond technology and time, e.g., individual vs. group decisions, systematically.
Marketing instruments	Knowledge accumulation and analysis of reproducibility, generalizability, and robustness of behavioral biases through meta-analyses.	Neumann and Böckenholt (2014); Tully and Winer (2014); Tarrahi et al. (2016)	Conduct a meta-analysis on the effects of time-inconsistent preferences on the adoption of new products.
	Behavioral biases concerning “place” as a marketing instrument.		Study behavioral biases in the face of online-offline convergence and newly emerging distribution channels.
Methodology	Field experiments to study behavioral biases in marketing with high external validity.	Lambrecht and Tucker (2015); Muchnik et al. (2013)	Analyze social influence bias on online platforms through ratings and reviews.
	Structural models to estimate key behavioral parameters.	DellaVigna (2018); Dubé et al. (2017)	Investigate uncertainty in the evaluation of product features via discrete choice experiments.
	Experimental designs for identifying behavioral biases as causal mechanisms.	Dubé et al. (2014); Imai et al. (2013)	Provide causal evidence for behavioral biases observed in observational data but not yet shown experimentally.
New technologies and business models	Effects of technological developments on behavioral biases.	Lambrecht and Tucker (2019)	Examine the potential of artificial intelligence (e.g., ad optimizing algorithms, recommendation systems) on inducing behavioral biases (e.g., overconfidence). Study the potential of augmented and virtual reality to induce the endowment effect in online shopping.
	Behavioral biases in the light of new business models.	Zervas et al. (2017)	Analyze behavioral biases in the Sharing Economy.
	New contexts creating potential new biases.	Dowling et al. (2018)	Conduct additional research on the pay-per-use “bias” in the car-sharing context.
Persistence, learning, and competition	Effects of competition on behavioral biases.	Pope and Schweitzer (2011); Hart and Moore (2008)	Study whether competition reduces or even reinforces behavioral biases (e.g., in the context of the Sharing Economy or taxi industry).
	Effect of persistence and learning on behavioral biases.	Miravete (2003)	Explore the effects of learning on behavioral bias over several periods, e.g., in lab experiments.

Table 2.6. Overview of future research avenues

that empirical generalizations can be derived and established from meta-analytic analyses. For example, Krishna et al. (2002) cover the effect of price presentations on perceived savings, Tarrahi et al. (2016) analyze fairness perceptions of price changes, Neumann and Böckenholt (2014) study loss aversion in product choice, Neumann et al. (2016) study context effects, Chernev et al. (2015) summarize research on choice overload, and Tully and Winer 2014 discuss WTP for socially responsible products. Given the increasing volume of marketing papers studying behavioral biases, there is demand for additional empirical generalizations and meta-analyses. For example, related to new product adoption, time-inconsistent preferences have been intensively studied in marketing contexts and, therefore, seem to be promising candidates.

Assessing the multiple developments and technological advancements discussed in the section on managerial implications, the marketing instrument place appears to be a particularly promising area for future research. For example, whether and how behavioral biases change could be analyzed in the context of the convergence of online and offline channels or the continuously increasing importance of mobile devices.

2.4.2.3 Methodology

Methodologically, the increased use of online and mobile channels offers researchers the possibility of gaining better observational data in terms of both quantity and quality and to more easily conduct field experiments, particularly in marketing (Lambrecht and Tucker 2015). Behavioral biases would be interesting to study with real consumers in field experiments. For example, most online platforms employ ratings and reviews on their websites. Such settings are particularly suitable for studying the effects of social influence bias (Muchnik et al. 2013). In addition, one could study how the application of real-time analytics and real-time decisions opens new opportunities for firms to respond directly to observed behavioral biases. We also strongly encourage using advances in experimental designs that explicitly allow for behavioral biases and help with identifying causal mechanisms in the future (see e.g., Dubé et al. 2014; Imai et al. 2013). Finally, applications of structural models are also highly valuable for future research because they allow the estimation of key behavioral parameters and counterfactual simulations (see e.g., Chung 2019; DellaVigna 2018; Dubé et al. 2017).

2.4.2.4 New Technologies and Business Models

New media and technologies affect behavioral biases during each of the four phases of consumers' purchase decision-making. Specifically, new media and technologies affect how consumers become aware of a need (e.g., smartphones and online social networks), their ability to search for and evaluate product alternatives (e.g., price comparison websites and consumer reviews), where and when they purchase (e.g., mobile and e-commerce), and their post-purchase behavior (e.g., reviews on social media). Given these technological developments, new behavioral biases may emerge, while existing behavioral distortions may play different roles in new contexts and environments. Therefore, whether the findings regarding the three classes of behavioral biases along the four phases need to be reevaluated in the future is unclear. For example, Lambrecht and Tucker (2019) show that algorithms may cause new biases. In their study, an algorithm optimizing cost-effectiveness in ad delivery leads to more exposure to men than women, although the ad was intended to be gender-neutral. This empirical regularity is replicated in other major online platforms.

Furthermore, developments accompanying new business models offer the potential for future research. For example, developments, such as the so-called "Sharing Economy", can change aspects of consumer behavior in each of the four phases (Eckhardt et al. 2019; Zervas et al. 2017). The shift from sole ownership to shared consumption renders other aspects of the transaction, such as interactions, trust, and flexibility, more important. Researchers could assess how behavioral biases could be used to help explain the unknown consumption patterns elicited by new business models. For example, prior research has provided substantial evidence that in many contexts, consumers prefer a flat-rate over a pay-per-use tariff, although they would have been better off under a pay-per-use tariff (flat-rate "bias"; e.g., Lambrecht and Skiera 2006). However, in support of our above argument, recent research indicates that consumers in a car-sharing context are rather prone to a so-called pay-per-use "bias" (Dowling et al. 2018).

2.4.2.5 Competition, Learning, and Persistence

Additionally, questions concerning the existence and persistence of behavioral biases in competitive environments are currently neglected. Some economists claim that behavioral biases are irrelevant because they cannot survive in competitive markets (Pope and Schweitzer 2011). However, behavioral economists argue that some biases may not only survive but may even be reinforced by competition (e.g., Hart and Moore 2008). In addition, because most markets are competitive, we believe that the behavioral biases discussed in the marketing literature also persist. Furthermore, this question would be interesting to combine with previously outlined research gaps, such as new business models through developments, such as those introduced by the Sharing Economy, or increased competition in several industries, such as the taxi industry. Therefore, these industries might be promising avenues for investigation. The same logic applies to the analysis of the persistence of biases, i.e., whether biases can exist over a longer period or whether learning occurs after several periods and biases are extinguished or attenuated. We discussed that experience must not necessarily result in less biased decisions. Although we are aware of situations in which experience leads consumers closer to the optimal decision (e.g., in tariff choice decisions; Miravete 2003), biases may persist when consumers attempt to avoid the stress caused by information that challenges their beliefs. It would be interesting to analyze the persistence of biases on a broader scale (especially biases with potentially large detrimental effects on consumers, such as overconfidence).

2.5 Conclusion

In this paper, we reviewed previous marketing research documenting behavior that deviates from the standard economic model and aggregated the findings using a structure that involves elements from both marketing and economics. We synthesized instructive marketing papers demonstrating how each class of behavioral biases can affect each phase of consumer purchase decision-making. By identifying nonobvious connections and differences within and across the four phases and three classes, we derive implications for marketing practice and future research.

We find a rich literature covering behavioral biases during the pre-purchase and purchase phases, whereas the marketing literature dedicated to behavioral biases during the need recognition and post-purchase phases is relatively scarce. We discuss possible explanations. We further note that the three classes of behavioral biases appear to be important to a different extent across phases. Nonstandard preferences play an important role in the pre-purchase and purchase phases. Similarly, nonstandard beliefs are also prominent during these phases, with an even greater relevance in the pre-purchase phase. Nonstandard decision-making seems to be relevant in all phases. Although we observe that some biases span multiple phases, we did not find any paper that systematically studies the interconnections or patterns of behavioral biases across all phases. This observation is surprising given that (1) relationships among biases across phases exist, (2) consumers can loop through the four phases multiple times (e.g., in the case of repeat purchases), and, depending on the product type, (3) the individual phases exert different weights of importance in purchase decision-making (e.g., consumables or durables). Similarly, the moderators of behavioral biases are under-researched in the marketing literature. We identified technology and time as moderators of biases. Regarding marketing instruments, we find that price and promotion are the two marketing instruments for which behavioral biases have been heavily studied in several phases of consumer purchase decision-making.

We presented specific implications for marketing practice and directions for future research. In particular, we debated behavioral biases (1) in digital and digitally enhanced environments, (2) in the context of big data and data analytics,

(3) with regard to marketing instruments, and (4) with respect to the potential negative consequences of exploiting them. Moreover, we proposed and discussed five different streams of future research. Specifically, we identified research directions and opportunities related to (1) the phases of consumer purchase decision-making and the classes of behavioral biases, (2) marketing instruments, (3) methodology, (4) new technologies and business models, and (5) competition, learning, and persistence. Marketing scholars possess the methods, tools, access to data, and relationships with companies to adequately examine the outlined research directions.

2.6 Appendix

For the interested reader, we provide a more detailed explanation of different biases within each of the three classes of deviations from the standard economic model (DellaVigna 2009): nonstandard preferences, nonstandard beliefs, and nonstandard decision-making. In particular, for each class of behavioral biases, we present corresponding tables (i.e., Table 2.7, Table 2.8, and Table 2.9), which provide examples of biases, direct readers to prominent articles on specific biases, as well as include a nonformal definition and an illustration of the respective biases (see e.g., Dhami 2016) for more formal and extended explanations of the behavioral biases). We further note that while we follow DellaVigna (2009) in separating the three classes of deviations, they are often interrelated.

Bias	**Example**	**Paper**	**Definition**	**Illustration**
Time-inconsistent preferences	Present bias; Hyperbolic discounting	Laibson (1997); Loewenstein and Prelec (1992); Thaler (1981)	Outcomes of near vs. distant future are more steeply discounted.	Choosing an apple today over two apples in two days, but two apples in a year and one day over an apple in a year.
Reference dependence	Reference points	Kahneman and Tversky (1979)	The utility function is defined relative to a reference point.	The value is derived from gains and losses rather than from final outcomes.
	Loss aversion	Kahneman and Tversky (1979)	The value function for losses is steeper than for gains.	People dislike losing 100€ more than they like gaining the same amount.
	Endowment effect	Thaler (1980); Kahneman et al. (1991)	Mere possession of an object increases its valuation.	People, initially given a product, have on average a higher valuation for it than people without the product.
	Nonlinear probability weighting	Allais (1953); Kahneman and Tversky (1979)	Small (large) probabilities are over- (under-)weighted.	Choosing to win 3,000€ with certainty over 4,000€ with a 0.8 chance, but choosing a lottery with a 0.2 chance of winning 4,000€ over a lottery with a 0.25 chance of winning 3,000€.
Social preferences	Other-regarding preferences	DellaVigna et al. (2012)	Individual value functions also depend on payoffs of others.	People engage in prosocial behavior, e.g., charitable giving or volunteering.
	Fairness concerns	Camerer and Thaler (1995); Fehr and Schmidt (1999); Fehr and Gächter (2000)	Individuals' decisions are often affected by fairness concerns, even if they reduce one's own payoffs.	In ultimatum games, where one player offers a portion of the money to another player, offers of less than 20% are deemed unfair and often rejected, so that neither player receives a payoff.

Table 2.7. Biases related to nonstandard preferences

Bias	Example	Paper	Definition	Illustration
Overconfidence	Overestimation	Weinstein (1980); Camerer and Lovallo (1999)	One's own actual capabilities, knowledge, or chances of success are systematically overestimated.	People tend to overestimate how much money they will save in the future or CEOs overestimate their ability to make good decisions.
	Overplacement	Svenson (1981); Larrick et al. (2007)	Relative to others, people think they are better.	In an experiment, in which subjects rated their driving skills, 93% indicated to be above the median.
	Overprecision	Daniel et al. (1998); Odean (1999)	The degree of certainty in one's own beliefs, predictions, and capabilities is too high.	Excessive rates of asset trading are potentially caused by the high degree of certainty investors have in their estimates of an asset's value.
Projection bias	Projection bias	Gilbert et al. (1998); Loewenstein (1996); Loewenstein et al. (2003)	Current preferences are projected into future states.	People project their current state of hunger into the future, ordering too much and unhealthy food for the next week.
Law of small numbers	Representativeness	Tversky and Kahneman (1971)	Small random samples are perceived as representative as large samples.	People tend to think that both a large and a small hospital will have an equal likelihood of reflecting the population proportion of 50% boys and girls born.
	Gambler's fallacy	Tversky (1974)	The belief that negative correlation exists in random processes.	In a coin toss, people think that after several occurrences of heads, tails will be more likely to occur next.
	Hot hand fallacy	Gilovich et al. (1985)	The belief that positive correlation exists in random processes.	People tend to believe that a basketball player's chance of hitting a shot are greater following a hit than following a miss.

Table 2.8. Biases related to nonstandard beliefs

Bias	**Example**	**Paper**	**Definition**	**Illustration**
Choice architecture	Framing effects	Loewenstein (1988); Meyerowitz and Chaiken (1987); Rabin (1998)	Equivalent decision problems that are framed differently, elicit different responses.	Women are more likely to conduct a breast self-examination when negative rather than positive consequences are stressed.
	Context effects	Huber et al. (1982); Huber and Puto (1983); Simonson (1989); Simonson and Tversky (1992); Tversky (1972)	The composition of the choice set affects consumer decisions by violating the assumptions of independence of irrelevant alternatives, regularity, and betweenness inequality.	In a two-product setting, the (relative) choice share of one focal product can be increased by introducing a third option, which is 1) an extreme option, making the focal product the middle option (compromise effect/extremeness aversion); 2) inferior to the focal option (attraction/asymmetric dominance/decoy effect); or 3) very similar to the competing option (similarity effect).
Limited attention	Inattention; Left-digit bias	Lacetera et al. (2012); Payne et al. (1992)	Some of the available information at no (or low) cost is over- (under-) weighted or ignored.	People tend to ignore the rightmost digits of numeric information, for example, when processing the mileage of used cars.
Persuasion and social pressure	Persuasion	Cain et al. (2005)	Beliefs of the information provider may have an excessive influence on individuals' attitudes and behavior.	Patients often do not account for their physician's conflict of interest in prescribing medication of a firm that finances their research, despite the disclosure of this information.
	Social pressure	Akerlof (1991); Milgram (1963)	Individuals may conform to the preferences of the relevant reference group (e.g., peers, family).	Cashiers in a supermarket are more productive if they know that high-productivity cashiers can observe them.
Emotions	Emotions	Ariely and Loewenstein (2006); Loewenstein (1996)	Emotions play a crucial role in individual decision-making but are not considered in the standard model.	Mood affects the amount of tipping in restaurants, hunger affects purchase behavior, and sexual arousal affects the likelihood of engaging in (morally) questionable behavior.

Table 2.9. Biases related to nonstandard decision-making

3 | When Zeros Count: Confounding in Preference Heterogeneity and Attribute Non-attendance [1]

Narine Yegoryan, Daniel Guhl, Friederike Paetz

Abstract

Consumer heterogeneity has been a prominent topic in choice modeling in marketing for many years. While the main focus has been on accounting for preference heterogeneity, few studies have recognized the importance of attribute non-attendance, i.e., when consumers consider only a subset of attributes in a purchase decision. We use a latent class model with continuous parameter distributions in each class to account for both attribute non-attendance and preference heterogeneity. Restrictive cases of this model, ignoring either attribute non-attendance or preference heterogeneity, enable us to investigate their possible confounding. Additionally, we contrast the model with models that allow more flexible forms of heterogeneity. Ten empirical applications indicate that biases arise in both cases, resulting in an overestimation of attribute non-attendance or biases in uncovered preference distribution. Furthermore, the magnitude of the bias depends on the share of indifferent consumers and ignored attributes. We find that the particular direction of the biases also depends on the type of the attribute, whether it is a feature allowing vertical or horizontal differentiation.

Keywords

Discrete choice modeling, Heterogeneity, Attribute non-attendance

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3.1 Introduction

Understanding consumer heterogeneity and identifying the distribution of consumer preferences is of utmost importance for marketers in a wide variety of decisions, including market segmentation and targeting, new product development, as well as pricing (Allenby and Rossi 1998; Allenby et al. 2014).

Most of the efforts in marketing literature have been focused on the development of models that accommodate consumer preference heterogeneity. First, the latent class model by Kamakura and Russell (1989) and later, the mixed multinomial logit (MMNL) model (e.g., McFadden and Train 2000) superseded the multinomial logit (MNL) model (McFadden 1974) as the new standard (Gilbride and Lenk 2010). Further advances have been made to account for even more flexible forms of preference heterogeneity by using a mixture of normals distribution (e.g., Allenby et al. 1998, Rossi et al. 2005, Burda et al. 2008), Dirichlet process prior, and more recently, Dirichlet process mixture (e.g., see Voleti et al. 2017). These models aim to accommodate multi-modal parameter distribution.

Nevertheless, consumers may differ not only in how much they value specific product attributes (i.e., preference heterogeneity) but also how they make decisions (Kamakura et al. 1996), and in particular, whether they value these attributes at all. The latter is of particular importance for marketers to understand and leverage. Consider a laptop manufacturer thinking about introducing a feature that allows the user to switch off the camera in its new model. Privacy concerned consumers should find this feature valuable. We would hardly expect anyone to derive a negative utility from this feature. However, some consumers may not care about this feature and ignore it when making a purchase decision. Consumers ignoring attribute information is commonly referred to as "attribute non-attendance" (ANA) in fields of transportation science and health economics[2]. Let us assume that around 20% of consumers do not care about the camera off switch (i.e., around 20% of ANA). We illustrate the potential distribution of preference parameters for this feature in the left-hand panel of Figure 3.1. The dashed black line represents the mean partworth utility (excluded zeros) and the solid black line – the density of the actual preference distribution.

If we neglect the fact that some consumers do not care about the feature, the uncovered (normal) distribution of preference parameters will be shifted, such that the mean will be biased towards zero and the variance – overstated (the red line in Figure 3.1). For simplicity, let us assume that all consumers have the same price sensitivity. The preference distribution in Figure 3.1 will then directly represent the distribution of consumers' willingness to pay (WTP). Consequentially, the laptop

[2] As much of the relevant literature comes from these fields, for the rest of the paper, we adopt this terminology.

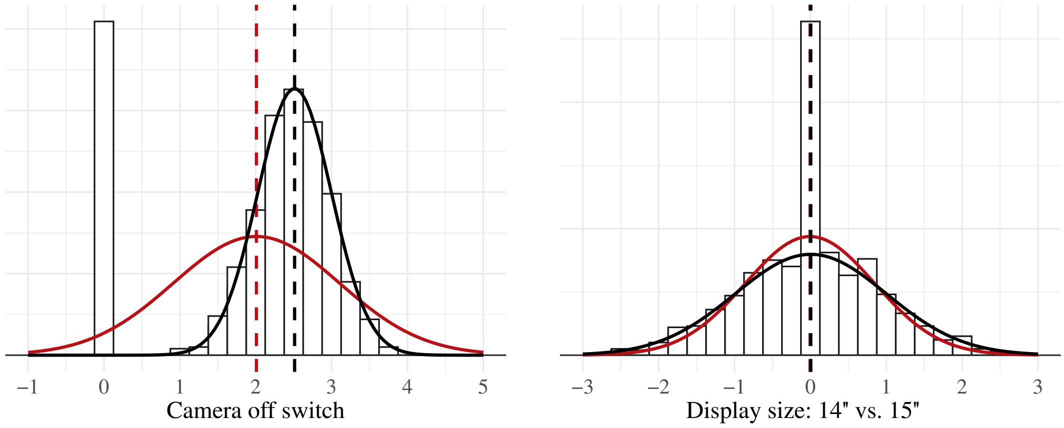


Figure 3.1. Potential biases when ignoring attribute non-attendance

manufacturer may overestimate the demand (as there is more mass on the positive domain under the red line) but underestimate the average WTP. At the same time, due to fatter tails of the implied distribution, the upper bound of the WTP may be overestimated. It is easy to imagine that if the actual parameter distribution would be further located to the right (i.e., further away from zero), we could expect an increase in the magnitude of the bias in both the mean and the variance of implied distribution when neglecting ANA. Similarly, an increase in the amount of ANA may lead to an increase in the magnitude of the bias.

Now consider that the laptop manufacturer is also interested in understanding preferences for display size of 14″ vs. 15″. Some consumers may prefer a smaller screen, while others – a larger one. We illustrate this example by plotting preference values on both positive and negative domains in the right-hand panel of Figure 3.1. Again, let us assume around 20% of ANA that is captured by precisely zero utility estimates. In this case, we do not observe much difference in the mean of the implied distribution that neglects ANA (the red line) and the actual distribution (the black line). However, the implied distribution has flatter tails and smaller variance. With an increase in the amount of ANA, we can expect the the tails of the implied distribution to get more flat, and the variance to get even smaller. As a result, the manufacturer may underestimate the overall amount of heterogeneity in preferences. Moreover, in efforts to target consumers with the highest WTP[3] for a particular display size (i.e., consumers on the tails of the preference distribution; Allenby and Ginter 1995), the manufacturer might underestimate how much these consumers are actually willing to pay.

ANA may arise due to various reasons. Consumers may ignore subsets of product attributes as they do not find them relevant (Gilbride et al. 2006), or they may be simplifying their decision due to its complexity and limited cognitive resources (Payne et al. 1992). In any case, ANA violates one of the underlying

[3]Again, assuming that all consumers have the same price sensitivity, the preference distribution in Figure 3.1 is a direct representation of the WTP distribution up to scale.

assumptions we make when modeling choice behavior, the assumption of full information processing. As different consumers may care about different subsets of attributes, this leads to differences in the composition of the utility function on the individual level. Identifying ANA and accounting for it in choice models is important. As we illustrate in the simple example above, otherwise, the estimated parameter distribution may be biased, leading to suboptimal marketing decisions.

Several approaches have been put forward that explicitly model ANA in marketing literature and adjacent fields of operation research, transportation science, and health economics. Some of these approaches only account for ANA but ignore preference heterogeneity (e.g., Hole 2011). Others simultaneously account for both ANA and preference heterogeneity (e.g., Gilbride et al. 2006; Hole et al. 2013). For example, Gilbride et al. (2006) propose a heterogeneous variable selection model in the Bayesian estimation framework. Hole et al. (2013) and Hess et al. (2013) apply a latent class approach similar to the consideration set model by Swait and Ben-Akiva (1987). Here, as many latent classes are defined as potential combinations of subsets of attributes that may be ignored. Hence, each class describes a specific attribute processing strategy. Maldonado et al. (2015) and Maldonado et al. (2017) apply feature selection tools from machine learning, particularly support vector machine algorithms, for inferring ANA.

In all these applications, models that account for ANA outperform their "standard" counterparts that operate under the assumption of full information processing. Several applications have reported biases in the estimates that may arise when models neglect ANA (e.g., Gilbride et al. 2006; Hess et al. 2013; Hole et al. 2013). In particular, all the applications find that mean estimates of preference distribution are biased towards zero in line with our simple illustration in Figure 3.1. Regarding the biases in the variance, findings in previous literature do not allow any generalizations. In a marketing application, Gilbride et al. (2006) find that the amount of heterogeneity is predominantly understated. Due to the proprietary nature of the data, we do not have information on the specific product category or attributes in this application. By contrast, in applications in the field of transportation science, where ANA is a much more prominent topic, often an overestimation of the amount of heterogeneity is reported (e.g., Hess et al. 2013; Collins 2012). These applications commonly deploy attributes for which a clear preference direction can be expected (e.g., price or time). In marketing applications, these are often attributes (as our example of the camera off switch feature for laptops) that allow firms to differentiate their products vertically (Draganska and Jain 2006). However, marketing applications also include such attributes as the brand, color, or as in our example, display size for laptops, for which parameter distribution can span both positive and negative domains. Such attributes allow firms to differentiate their products horizontally (Draganska and Jain 2006). We expect that for these attributes, we would observe the variance and, therefore, the amount of heterogeneity to be underestimated when neglecting ANA, as illustrated in our simple example for display size of laptops (the right-hand panel in Figure 3.1). Therefore, this paper aims to examine the direction and the magnitude of biases in the estimated mean and variance of parameter distribution when ANA is neglected.

Furthermore, Hess et al. (2013) and Hole et al. (2013) outline that biases may also arise when models account for ANA but neglect preference heterogeneity. In particular, they find that assuming homogeneous preferences across respondents may lead to an overstatement of ANA, as consumers with low sensitivity to an attribute might be treated as having zero sensitivity. Hess et al. (2013) and Hole et al. (2013), in their applications in the context of route choice and prescription drug choice, respectively, find that after accounting for preference heterogeneity, the amount of uncovered ANA either considerably decreases or completely diminishes. By contrast, Gilbride et al. (2006), in an unknown product choice context, and Yegoryan et al. (2020), in their application in the context of choices for coffee makers and laptops, find probabilities of ANA that exceed 45%. Due to the limited number of applications, it remains a question if ANA prevails in different marketing contexts. In particular, there is a considerable variation when it comes to consumer involvement, the stakes or financial risk of the purchase, and the complexity of the decisions in marketing contexts. Hence, this paper aims to understand ANA's prevalence in different contexts, settings, and attributes.

In summary, in this paper, we aim at a deeper understanding of the potential confounding of preference heterogeneity and ANA. In particular, our objective is to shed more light on the direction and the magnitude of biases we can expect for different types of attributes. Building upon previous literature and as outlined in the illustrative example, we expect that the amount of ANA and the location of the actual preference distribution with respect to zero will affect the magnitude of the bias in the mean and both the direction and the magnitude of the bias in the variance of preference distribution. For this purpose, we set out to compare various models that account for neither preference heterogeneity nor ANA, only ANA or preference heterogeneity, or both in different empirical applications. Our primary focus is understanding the different patterns of preferences different models can identify.

We utilize ten different datasets from choice-based conjoint (CBC) studies conducted in the context of durable products (e.g., laptops), fast-moving-consumer goods (e.g., packaged orange juice), as well as entertainment and experiential goods and services (e.g., video-streaming services). Purchase decisions in these various contexts carry different financial risks (choosing a package of orange juice is a low stake decision compared to choosing a laptop). The datasets also include a different number of attributes and therefore vary in the complexity of the decision. Consumer involvement and the stakes of the choice decision have long been recognized to affect consumers' information search (e.g., Laurent and Kapferer 1985), and, therefore, may drive ANA. Furthermore, complexity and information overload may also prompt consumers to ignore some information in the decision-making (e.g., Payne et al. 1992, Bettman et al. 1998, Orquin et al. 2013). Hence, differences in these characteristics of the datasets also enable us to examine the prevalence of ANA in various purchase situations.

The rest of the paper is structured as follows. In the next section, we describe the methodology, including the models we are interested in comparing and the estimation procedure. In section 3.3, we start by presenting in more detail our ten empirical applications and their characteristics. We then discuss our findings, including the comparison of in- and out-of-sample model fit and the effects of ignoring either preference heterogeneity or ANA. Finally, we outline managerial implications and conclude with a summary and an outline of avenues for future research.

3.2 Methodology

We start this section by describing the standard multinomial logit (MNL) model (McFadden 1974). We then proceed to describe the models that build upon and extend the MNL model to account for (flexible) forms of unobserved preference heterogeneity and ANA (see Elshiewy et al. 2017 for a comprehensive review on MNL models in marketing). We conclude the section by discussing the estimation procedure.

3.2.1 Multinomial Logit Model

The utility individual i $(i = 1, \ldots, I)$ obtains from alternative j $(j = 1, \ldots, J)$ in choice task t $(t = 1, \ldots, T)$ is given by:

$$U_{ijt} = x_{ijt} \cdot \beta + \epsilon_{ijt}, \tag{3.1}$$

where x_{ijt} is a K-dimensional row vector of attribute values describing alternative j in choice task t for individual i, β is a column vector of corresponding preference parameters, which are homogeneous across consumers, and $\epsilon_{ijt} \sim$ i.i.d type I extreme value error term. Given the distributional assumptions of the error term, the probability of individual i choosing alternative j in choice task t has the following closed-form:

$$P_{ijt} = \frac{\exp(x_{ijt} \cdot \beta)}{\sum_{j' \in J} \exp(x_{ij't} \cdot \beta)}, \tag{3.2}$$

leading to the following likelihood function for individual i:

$$L_i = \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt}^{y_{ijt}}, \tag{3.3}$$

where y_{ijt} is a dummy indicating whether individual i chose the alternative j in choice task t.

3.2.2 Models Accounting for Preference Heterogeneity

To account for unobserved preference heterogeneity, we can extend the MNL model by assuming that preference parameters are individual-specific, which can be denoted by adding the i index to β_i in Equation (3.1). Assuming that β_i are draws from a particular continuous distribution (e.g., normal, log-normal, truncated; McFadden and Train 2000, Train 2009) and retaining the distributional assumptions on the error term, the mixed multinomial logit (MMNL) model is derived. As commonly done (Keane and Wasi 2013), we assume that β_i is distributed multivariate normal with mean $\bar{\beta}$ and covariance Σ, i.e., $\beta_i \sim N(\bar{\beta}, \Sigma)$ with coefficients being constant over T.

In the MMNL model, choice probabilities are defined as

$$P_{ijt} = \int \frac{\exp(x_{ijt} \cdot \beta_i)}{\sum_{j' \in J} \exp(x_{ij't} \cdot \beta_i)} \phi(\beta_i | \bar{\beta}, \Sigma) d\beta_i, \tag{3.4}$$

and the likelihood function can be written as

$$L_i = \int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt}^{y_{ijt}} \phi(\beta_i | \bar{\beta}, \Sigma) d\beta_i. \tag{3.5}$$

Note that by setting all the elements of Σ to zero, the MMNL model reduces to the standard MNL model with homogeneous preferences. The first applications of the MMNL became only possible after the development of simulation methods (McFadden and Train 2000). Since then, the MMNL model has replaced the MNL model as the standard and become one of the most popular models used (Elshiewy et al. 2017).

Further extensions of the model have been proposed that allow capturing even more flexible forms of heterogeneity. We will mainly focus on the "mixed-mixed" multinomial logit (MMMNL) model[4], which assumes that the mixing distribution of β_i is a discrete mixture of normals, i.e., $\beta_i \sim N(\bar{\beta}_q, \Sigma_q)$ with w_q as the probability of class q $(q = 1, \ldots, Q)$, $\sum_{q=1}^{Q} w_q = 1$ and $w_q > 0 \; \forall q$. Class probabilities w_q can be

[4] We adopt the terminology used by Keane and Wasi (2013).

modeled as:

$$w_q = \frac{\exp(w_q^*)}{1 + \sum_{q=2}^{Q} \exp(w_q^*)}. \tag{3.6}$$

where w_q^* is a vector of class specific intercepts. Note that this specification ensures that $\sum_{q=1}^{Q} w_q = 1$ (Keane and Wasi 2013).

In the MMMNL model, the choice probability of individual i for alternative j in the choice task t is a weighted sum across classes:

$$P_{ijt} = \sum_{q=1}^{Q} w_q \cdot \int \frac{\exp(x_{ijt} \cdot \beta_{i|q})}{\sum_{j' \in J} \exp(x_{ij't} \cdot \beta_{i|q})} \phi(\beta_{i|q}|\bar{\beta}_q, \Sigma_q) d\beta_{i|q}, \tag{3.7}$$

where $\phi(\beta_{i|q}|\bar{\beta}_q, \Sigma_q)$ is the normal density with mean $\bar{\beta}_q$ and Σ_q in class q. Hence, the likelihood function for individual i is given by

$$L_i = \sum_{q=1}^{Q} w_q \cdot \int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt}^{y_{ijt}} \phi(\beta_{i|q}|\bar{\beta}_q, \Sigma_q) d\beta_{i|q}. \tag{3.8}$$

Note that the MMMNL model necessitates estimating additional $(Q-1)$ class parameters. If w_q for all but one class tends to zero, the MMMNL model reduces to the MMNL model. In general, the MMMNL can approximate any distribution arbitrary well (Keane and Wasi 2013). It has been shown to outperform the MMNL model both in- and out-of-sample (e.g., Keane and Wasi 2013, Rossi et al. 2005, Burda et al. 2008, as well as Voleti et al. 2017). Moreover, Keane and Wasi (2013) find that the MMMNL model can capture more "extreme" patterns of consumer behavior, such as the use of lexicographic rules, as well as "random" behavior.

3.2.3 Models Accounting for Attribute Non-attendance

In this section, we describe the models that account for ANA. In particular, we start with the endogenous attribute attendance (EAA) model proposed by Scarpa et al. (2009) and Hole (2011). The EAA model is a confirmatory latent class approach (Hess et al. 2013). It builds upon the MNL model but introduces a structure by a priori defining latent classes, which describe all potential combinations of attribute processing strategies, that can account for people ignoring some information. Given K attributes, 2^K latent classes are defined. In each class s $(s = 1, \ldots, S)$, the specific attribute processing strategy can be described by a K-dimensional column vector $\lambda_s = [\lambda_{s1}, \ldots, \lambda_{sK}]'$, where λ_{sk} is a dummy indicating whether class s included attribute k $(\lambda_{sk} = 1)$ or not $(\lambda_{sk} = 0)$. Accordingly, the model implies a class-specific utility function:

$$U_{ijt|s} = x_{ijt} \cdot \beta_s + \epsilon_{ijt}, \tag{3.9}$$

with $\beta_s = \lambda_s \circ \beta$, τ_s as the probability of class s, $\sum_{s=1}^{S} \tau_s = 1$, and $\tau_s > 0\ \forall s$. As in Equation (3.1), β is a column vector of preference parameters. However, through the elementwise multiplication (denoted by $\circ$) with the indicator vector λ_s, parameters for attributes that are not included in class s are set to zero, resulting in a class-specific vector of parameters β_s. For accommodating categorical attributes, effects coding should be used[5]. Moreover, as now multiple elements in x_{ijt} will be related to an attribute, the λ_s vector should be extended and mapped onto the correct parameter dimensions. If attribute k is ignored, then all its m_k levels are ignored, and all the corresponding λ_s elements should be set to zero.

As parameters are switched on and off, a different linear (additive) utility function characterizes each class. The EAA model accommodates several decision rules, including full compensatory, when all attributes are attended, semi-compensatory, when two or more but not all attributes are attended, (a probabilistic version of) lexicographic rule, when only one attribute is attended, and the random choice, when none of the attributes is attended.

Retaining the distributional assumptions of the error term, the choice probability of individual i of alternative j in choice task t is now conditional on class s:

$$P_{ijt|s} = \frac{\exp(x_{ijt} \cdot \beta_s)}{\sum_{j' \in J} \exp(x_{ij't} \cdot \beta_s)}. \tag{3.10}$$

We can, of course, define the submodel of class probabilities as in Equation (3.6). However, it would require estimating $(S-1)$ additional class parameters. As $S = 2^K$, it is increasing exponentially with the increase in the number of attributes. Already with $K = 6$ attributes, a typical case in CBC studies (Rao 2014), we would end up with 63 additional parameters. Such operationalization may reduce model stability and result in only marginal improvements in fit due to loss of parsimony (Hess et al. 2013).

In contrast, we follow Hole (2011) and make a more restrictive assumption that the probability of attending one attribute is independent of the probability of attending another attribute. While such an assumption, which Hole (2011) refers to as independence of attribute attendance (IAA) assumption, may seem restrictive, it results in a more parsimonious model. More specifically, by utilizing the IAA

[5] Note that dummy coding for categorical attributes is not appropriate in these types of models (Gilbride et al. 2006). The zero value of the preference parameter has a particular meaning in the EAA model, which is the attribute is ignored. In the case of dummy coding, though, the estimate of the base level is automatically set to zero.

assumption, we can model the class probabilities τ_s as a mapping from attribute attendance probabilities π_k, which are parametrized as a logistic function:

$$\tau_s = \prod_{k=1}^{K} \pi_k^{\lambda_{sk}} \cdot (1-\pi_k)^{1-\lambda_{sk}}, \quad \text{with} \quad \pi_k = \frac{\exp(\gamma)}{1+\exp(\gamma)}, \tag{3.11}$$

where γ is a K-dimensional row vector of attribute-specific intercepts. The specification in Equation (3.11) is closely related to the model of choice set heterogeneity of Swait and Ben-Akiva (1987), as well as to concomitant latent class models of Kamakura et al. (1994). In general, it is possible to include individual-specific covariates in the submodel of class probabilities. For example, Hole et al. (2013) and Collins et al. (2013) use the respondents' stated measure of ANA, Yegoryan et al. (2020) use a visual attention measure derived from eye tracking.

We can write the unconditional choice probability as a weighted sum of class-specific choice probabilities defined in Equation (3.10):

$$P_{ijt} = \sum_{s=1}^{S} \tau_s \cdot P_{ijt|s}, \tag{3.12}$$

and the likelihood of individual i as

$$L_i = \sum_{s=1}^{S} \tau_s \cdot \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|s}^{y_{ijt}}. \tag{3.13}$$

By setting $\tau_s = 1$ for the class where all attributes are attended, the EAA model reduces to the MNL. Hence, the EAA model nests the MNL at the boundary condition $\gamma \to \infty$.

The EAA model can be further extended to account for both attribute non-attendance and preference heterogeneity. In particular, we follow Hess et al. (2013) and Hole et al. (2013), and assume that preference parameters are distributed multivariate normal (i.e., $\beta_i \sim (\bar{\beta}, \Sigma)$) across the latent classes.

While the parameter distribution is common across the latent classes, each class is related to a different subset of attended attributes and, therefore, has a different vector of parameters due to elementwise multiplication with γ_s: $\beta_{i|s} = \beta_i \circ \gamma_s$. Hence, the choice probabilities can be written as

$$P_{ijt} = \sum_{s=1}^{S} \tau_s \cdot \int \frac{\exp(x_{ijt} \cdot \beta_{i|s})}{\sum_{j' \in J} \exp(x_{ij't} \cdot \beta_{i|s})} \phi(\beta_i | \bar{\beta}, \Sigma) d\beta_i, \tag{3.14}$$

and the likelihood of individual i as

$$L_i = \sum_{s=1}^{S} \tau_s \cdot \int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|s}^{y_{ijt}} \phi(\beta_i|\bar{\beta}, \Sigma) d\beta_i. \tag{3.15}$$

Note that by setting all elements of Σ to zero, the MEAA model reduces to the EAA model. By setting $\tau_s = 1$ for the class where all attributes are included, the MEAA model reduces to the MMNL model. Lastly, applying both restrictions, reduces the MEAA model to the bare bones MNL model, with neither type of heterogeneity accommodated. The MEAA model has some similarities to the MMMNL model, as both should be able to capture lexicographic and random choice behavior. However, the MMMNL and the MEAA models may excel at capturing different patterns in preference distribution. The MEAA model is specifically designed to capture and disentangle the genuinely zero estimates. On the other hand, the MMMNL may be better at identifying cases where the preference distribution is multi-modal.

3.2.4 Estimation Procedure

We split all the datasets into estimation (training) and holdout (validation) samples. More specifically, for each respondent in each dataset, we randomly selected two choice tasks as holdout tasks. For each of the datasets, we estimated five models, MNL, EAA, MMNL, MEAA, and MMMNL, using the corresponding training sample. For statistical inference, we employed maximum likelihood estimation with sample log-likelihood $LL(\theta) = \sum_{i \in I} ln(L_i)$, where L_i denotes the likelihood of individual i given by Equation (3.3), (3.13), (3.5), (3.15), and (3.8) for the MNL, EAA, MMNL, MEAA, and MMMNL models, respectively. θ represents the vector of parameters to be estimated. To retain parsimony, for heterogeneous models, we used a diagonal specification of Σ. For MMMNL models, we specified Q = 2 classes[6]. Note that in the case of heterogeneous models, an integration over the density of taste parameters is required for which we adopted the simulated maximum likelihood approach using 500 Halton draws and gradient-based Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Train 2009).

We have tested multiple starting values for the models and report the one with the best log-likelihood value. As MMMNL models are prone to pick up extreme behavior and result in unrealistically large parameter values (Keane and Wasi 2013), we applied similar constraints to the parameter values as in Keane and Wasi (2013) post estimation. More specifically, we consider only the subset of the models estimated based on different starting values, in which absolute values of the utility

[6]We have tested the Q = 3 specification as well. However, we did not find improvements in BIC for any of the datasets. Also Keane and Wasi (2013) find that in many other applications of the MMMNL two-class specification usually results in better BIC.

estimates (both mean and standard deviation) do not exceed 20 and class weights are within $(-5, 5)$ interval (i.e., the class probability is at least around 1%).

For the out-of-sample predictions, we use individual-level conditional estimates in all models, except for the MNL. In the MNL model, all preference parameters are homogeneous across the sample. For the heterogeneous models, we employ Bayes' rule to condition on the observed choices and compute the posterior means of the individual-level preference parameters $\beta_i^{\text{post.}}$ (see Train 2009, ch.11 for details). Correspondingly, for the MMNL model, individual-level parameters are given by

$$\beta_i^{\text{post.}} = \frac{\int \beta_i \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt}^{y_{ijt}} \phi(\beta_i|\bar{\beta}, \Sigma) d\beta_i}{\int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt}^{y_{ijt}} \phi(\beta_i|\bar{\beta}, \Sigma) d\beta_i}, \tag{3.16}$$

and in the MMMNL model by

$$\beta_i^{\text{post.}} = \sum_{q=1}^{Q} w_{iq} \cdot \frac{\int \beta_{i|q} \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|q}^{y_{ijt}} \phi(\beta_{i|q}|\bar{\beta}_q, \Sigma_q) d\beta_{i|q}}{\int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|q}^{y_{ijt}} \phi(\beta_{i|q}|\bar{\beta}_q, \Sigma_q) d\beta_{i|q}}. \tag{3.17}$$

In the case of the EAA and the MEAA models, the vector of preference parameters is (also) conditional on the individual's class allocation:

$$\tau_{is}^{\text{post.}} = \frac{\tau_s \cdot L_{i|s}}{\sum_{s' \in S} \tau_{s'} \cdot L_{i|s'}}. \tag{3.18}$$

As the central behavioral assumption of the ANA models (i.e., the EAA and the MEAA), is that each individual has a specific attribute processing strategy, we opt for a nonoverlapping segmentation and assign each individual to the class s^* with the highest value of $\tau_{is}^{\text{post.}}$ (cf. Desarbo et al. 1995). We then compute the individual-level conditional estimates as

$$\beta_i^{\text{post.}} = \lambda_{is^*} \circ \bar{\beta}, \tag{3.19}$$

for the EAA model. For the MEAA model:

$$\beta_{is^*}^{\text{post.}} = \frac{\int \beta_{is^*} \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|s^*}^{y_{ijt}} \phi(\beta_i|\bar{\beta}, \Sigma) d\beta_i}{\int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|s^*}^{y_{ijt}} \phi(\beta_i|\bar{\beta}, \Sigma) d\beta_i}. \tag{3.20}$$

Yegoryan et al. (2020) show that such "crisp" segmentation works rather well: despite the high number of classes, most of the time, the posterior probabilities strongly favor one class for an individual.

For the MMNL, MMMNL, and MEAA models, we again employ simulation methods with Halton draws to approximate the integrals in Equations (3.16), (3.17), and (3.20), respectively.

3.3 Empirical Applications

3.3.1 Data

For the empirical application, we utilize a broad set of ten different datasets from CBC studies on different product categories, including fast-moving consumer goods (FMCG) such as smoothies and packaged orange juice, entertainment and experiential products and services such as video-streaming services, basketball tickets, (student) parties, and holiday destinations, as well as consumer electronics such as electric kettles, laptops, tablets, and cameras.[7] These studies differ significantly in terms of the financial risk or stakes of the decision in question. For example, in the case of electronic goods in our set, laptops, tablets, and cameras are more expensive: priced up to $749, 550€, and $279 in the studies, respectively. On the other hand, electric kettles are priced up to $80 in the study. Hence, we classify the former three as relatively high-risk categories, and the latter as a relatively low-risk category. In a similar vein, the choice of holiday destinations, which costs up to $1200 in the study, is a high-stake decision.

In contrast, smoothies and orange juices, which are priced up to 1.99€ and 1.89€ in the studies, respectively, we consider being relatively low-risk categories. Regarding entertainment goods, we argue that the choice of a video-streaming service, with alternatives priced up to $12.99, and which party to attend, with alternatives priced up to 7€, is a relatively low-stake decision. In contrast, basketball tickets are priced up to 30€ in the study. We, therefore, are more inclined to classify the latter as a relatively high-risk category.

Our classification provides us with more context to investigate the patterns of ANA across different datasets. Moreover, price, which indicates the financial risk of the purchase, is related to product category involvement (Laurent and Kapferer 1985). Several of the developed scales for measuring involvement that account for its multifaceted nature, e.g., in Laurent and Kapferer (1985), Jain and Srinivasan (1990), and McQuarrie and Michael (1986), include risk as an essential dimension.

Furthermore, within each (high or low) risk or stake classification, the studies vary in the number of attributes ranging from 3 to 8. The number of attributes serves as an indicator of the degree of complexity of the decision task (Dellaert et al. 2012). Of course, other important factors contribute to the complexity of the decision task, such as the number of alternatives, the number of attribute levels, the similarity of the alternatives (Dellaert et al. 2012). However, as in CBC studies

[7]Please note that except for Parties and Electric kettles, all other datasets have been formerly published. For more details on these studies, we kindly refer the reader to the respective source highlighted in Table 3.1.

	Category	Source	Risk/Stake	Attributes (No. levels)		ANA-Classes	No. Alt.	Obs. = id × cs
1.	Smoothies	Paetz and Steiner (2017)	low	3 attr.:	brand (4), price (4), packaging (4)	8	3 + none	$8910 = 495 \times 18$
2.	Orange juice	Paetz and Guhl (2017)	low	4 attr.:	brand (4), price (4), packaging (2), fairtrade label (2)	16	3 + none	$5472 = 342 \times 16$
3.	Video-streaming services	Glasgow and Butler (2017)	low	5 attr.:	privacy policy (3), price (4), catalog size (3), fast content (2), commercials shown (2)	32	4 + none	$2860 = 260 \times 11$
4.	Parties	our dataset	low	6 attr.:	location (6), drinks (3), dress code (2), specials (3), music (4), price (2)	64	3 + none	$2120 = 212 \times 10$
5.	Electric kettles	our dataset	low	7 attr.:	brand (3), capacity (3), material (3), power (2), variable temperature (2), Amazon rating (3), price (4)	128	3 + none	$2624 = 164 \times 16$
6.	Basketball tickets	Schlereth and Skiera (2017)	high	3 attr.:	price category (4), price (4), additional features (3)	8	4 + none	$1920 = 160 \times 12$
7.	Laptops	Liu and Tang (2015)	high	4 attr.:	display size (3), memory (3), hard drive (3), price (3)	16	3	$1800 = 120 \times 15$
8.	Tablets	Schlereth and Skiera (2017)	high	6 attr.:	brand (3), price (4), display size (2), battery (2), resolution (2), storage capacity (3)	64	3 + none	$2484 = 207 \times 12$
9.	Cameras	Allenby et al. (2014)	high	7 attr.:	brand (4), pixel (2), zoom (2), video (2), swivel (2), WiFi (2), price (5)	128	4 + none	$5312 = 332 \times 16$
10.	Holiday destinations	Keane and Wasi (2013)	high	8 attr.:	airline (2), local tours (2), destination (2), length of stay (2), meal inclusion (2), peak season (2), price (2), accommodation (2)	256	2	$5296 = 331 \times 16$

Table 3.1. Sources and characteristics of the datasets

using 3-4 alternatives is rather common (Rao 2014), we focus on the number of attributes as one primary driver of complexity[8].

In summary, the ten datasets allow us to descriptively investigate whether ANA prevails and how it varies across different product categories and settings. We summarize the main characteristics and the sources of the datasets in Table 3.1 (for details on the attribute levels see Appendix A).

Both CBC studies, on choices of parties and electric kettles, have been designed and administered using Sawtooth Software.[9] The CBC study on parties was conducted in 2010 at a large German university using a convenience sample of students. The CBC study in the context of electric kettles was conducted in December 2019 - January 2020, using a crowdsourcing platform Amazon Mechanical Turk.[10] To ensure the quality of the responses, in the case of the Electric kettles dataset, we have used a qualification question, which required the respondents to solve a simple math problem at the very beginning of the questionnaire, as well as three attention questions evenly distributed across the questionnaire. We have only included respondents who passed the qualification question, answered correctly to all three attention questions, and took more than one minute (the 5%-Quantile in the response time) to complete all the choice tasks.

For formerly published datasets, we have used the data pruning steps reported by the authors where this was necessary. Note that some but not all datasets include holdout tasks. To ensure we retain consistency across datasets, we have only included the main tasks in our analysis. Furthermore, in all datasets, we have additionally excluded respondents who have selected the "none" option in all the main tasks.[11] In Table 3.1, we report the number of respondents after the data pruning and the number of main choice tasks (initial holdout tasks excluded).

[8]From hereon, we use complexity and the number of attributes as equivalents.

[9]In both cases, we used complete enumeration as a method for generating random tasks, which ensures minimal overlap between concepts in a task and strives for the most nearly orthogonal design (Sawtooth Software 2017). Additionally, multiple versions have been generated and randomized between respondents.

[10]We recruited participants on this platform that resided in the US and had more than 1000 HITs approved with a 95% approval rating. The respondents have been paid fair compensation for their time computed based on an $8 hourly wage.

[11]Accordingly, we excluded one respondent in the Electric kettles and Parties datasets, two respondents in the Smoothie dataset, and seven respondents in the Tablets dataset.

3.3.2 Model Comparison

We compare the estimated models' in-sample performance in terms of the log-likelihood (LL) values and the Bayesian information criterion (BIC)[12], which penalizes for model complexity. We summarize the results in Table 3.2.

In all datasets, as expected, the MNL is the worst performing model in terms of both LL and BIC. Accounting for either ANA or preference heterogeneity substantially increases the in-sample model performance: both EAA and MMNL models outperform the MNL model indicated by both LL and BIC. However, accounting only for preference heterogeneity yields greater in-sample improvements than accounting only for ANA across our ten datasets: the MMNL model outperforms the EAA model for all datasets. Nevertheless, accommodating both ANA and preference heterogeneity is essential: the MEAA model outperforms both the EAA model and the MMNL model. In particular, the MEAA model outperforms the MMNL in terms of LL in all ten and BIC in 8 out of 10 datasets. For the datasets Parties and Laptops, the BIC of the MEAA model is only respectively 1.280 and 5.158 points higher than the BIC of the MMNL model. According to Raftery (1995), only a difference of more than 10 points provides evidence to favor the model with better BIC.

Even when considering the MMMNL model, which accommodates a more flexible pattern of preference heterogeneity, we see that 8 out of 10 times the MEAA model is the best based on BIC and 2 out of 10 times also based on LL. It is notable that while the MMMNL model is mostly the best in LL, the difference in LL between the MMMNL and the MEAA models is not large. Considering the small improvements in LL and a rather substantial increase in the number of parameters in the MMMNL model, it is no surprise that the MEAA model does much better on BIC, i.e., when we penalize for model complexity.

Furthermore, the out-of-sample predictive validity measured by hit rate and hit probability is presented in Table 3.3. The results uncover some interesting patterns. First, the models that account for ANA (i.e., the EAA and the MEAA), considerably outperform their counterparts that only account for preference heterogeneity (i.e., the MNL and MMNL). In particular, the EAA model has a much higher hit rate (mean difference of 17 percentage points (PP)) and hit probability (mean difference of 10PP) in all datasets compared to the MNL model. Also, the MEAA model mostly outperforms the MMNL: in 8 out of 10 times in hit rate (mean difference of 4PP) and in all cases in hit probability (mean difference of 3PP). Second, the EAA model outperforms all the models in two datasets in the hit rate (Laptops

[12]Note that BIC can be used for the comparison of non-nested models. As MEAA model nests MNL, EAA, MMNL at the boundary of the parameter space, and MEAA and MMMNL are not nested, the log-likelihood ratio test is not applicable (McLachlan and Peel 2000).

Dataset		MNL	EAA	MMNL	MEAA	MMMNL
Smoothies	LL	−7931.836	−6945.037	−6233.871	−5863.345	**−5806.924**
	BIC	15935.457	13988.779	12611.311	**11897.179**	11909.960
		(8)	(11)	(16)	(19)	(33)
Orange juice	LL	−5083.525	−4575.238	−4049.225	−3880.148	**−3836.181**
	BIC	10226.366	9243.689	8217.085	**7912.826**	7918.105
		(7)	(11)	(14)	(18)	(29)
Video-streaming services	LL	−3591.151	−3278.248	−3264.935	−3167.175	**−3161.749**
	BIC	7244.365	6657.350	6653.997	**6497.266**	6579.509
		(8)	(13)	(16)	(21)	(33)
Parties	LL	−2016.365	−1924.861	−1771.785	−1750.117	**−1713.113**
	BIC	4144.269	4005.879	**3766.651**	3767.931	3879.824
		(15)	(21)	(30)	(36)	(61)
Electric kettles	LL	−2380.627	−1963.627	−1870.294	**−1753.577**	−1780.361
	BIC	4854.121	4074.293	3926.323	**3747.061**	3939.930
		(12)	(19)	(24)	(31)	(49)
Basketball tickets	LL	−1959.438	−1561.666	−1370.051	−1350.408	**−1303.796**
	BIC	3976.114	3202.033	2854.576	**2836.755**	2843.694
		(8)	(11)	(16)	(19)	(33)
Laptops	LL	−1239.081	−1034.992	−992.023	−979.897	**−969.003**
	BIC	2529.628	2150.861	**2086.979**	2092.137	2151.227
		(7)	(11)	(14)	(18)	(29)
Tablets	LL	−2414.468	−2142.529	−1952.786	−1926.379	**−1846.543**
	BIC	4897.653	4399.588	4043.007	4036.004	**3975.592**
		(9)	(15)	(18)	(24)	(37)
Cameras	LL	−5701.867	−4958.032	−4341.663	**−4131.948**	−4145.621
	BIC	11488.175	10059.614	8852.210	**8491.890**	8637.455
		(10)	(17)	(20)	(27)	(41)
Holiday destinations	LL	−2686.871	−2395.588	−2262.399	−2172.046	**−2160.810**
	BIC	5441.272	4926.234	4659.856	**4546.680**	4600.179
		(8)	(16)	(16)	(24)	(33)
Frequency:						
	Best LL	0	0	0	2	**8**
	Best BIC	0	0	2	**7**	1

Notes: The number of parameters in each model for each dataset is presented in parentheses. Values in bold indicate the best performing model for a given dataset based on a given criterion (LL or BIC).

Table 3.2. Model comparison: In-sample measures

and Holiday destinations). Potentially, such a result indicates that in these cases understanding whether an attribute is ignored or not, i.e., whether the parameter is zero or not, is more informative than trying to estimate the precise values of non-zero parameters. This could happen if the actual amount of heterogeneity is rather small. Third, the MEAA model mostly remains the best performing model out-of-sample: it outperforms all the models in hit rate and hit probability in 5 and 7 out of 10 cases, respectively. In six cases, when the MEAA is superior to

Dataset		MNL	EAA	MMNL	MEAA	MMMNL
Smoothies	hit rate	0.582	0.756	0.740	**0.787**	0.765
	hit probability	0.466	0.556	0.662	**0.704**	0.700
Orange juice	hit rate	0.572	0.658	0.734	**0.778**	0.753
	hit probability	0.436	0.528	0.655	**0.697**	0.689
Video-streaming services	hit rate	0.356	0.740	0.481	**0.760**	0.483
	hit probability	0.236	0.329	0.360	**0.408**	0.388
Parties	hit rate	0.498	0.594	**0.623**	0.594	0.597
	hit probability	0.356	0.431	0.520	**0.558**	0.532
Electric kettles	hit rate	0.543	0.683	0.729	**0.768**	0.726
	hit probability	0.423	0.540	0.639	**0.678**	0.650
Basketball tickets	hit rate	0.316	0.659	0.662	0.647	**0.678**
	hit probability	0.230	0.411	0.584	0.592	**0.613**
Laptops	hit rate	0.633	**0.767**	0.746	0.758	0.746
	hit probability	0.528	0.654	0.700	0.712	**0.713**
Tablets	hit rate	0.536	0.606	0.664	0.667	**0.679**
	hit probability	0.378	0.480	0.576	0.598	**0.611**
Cameras	hit rate	0.489	0.616	0.700	**0.732**	**0.732**
	hit probability	0.362	0.464	0.607	**0.645**	0.638
Holiday destinations	hit rate	0.701	**0.831**	0.802	0.816	0.811
	hit probability	0.603	0.690	0.751	**0.769**	0.766
Frequency:						
	Best hit rate	0	2	1	**5**	3
	Best hit probability	0	0	0	**7**	3

Notes: Values in bold indicate the best performing model for a given dataset based on a given criterion (hit rate or hit probability).

Table 3.3. Model comparison: Out-of-sample measures

the MMMNL model, it offers an average of 6PP better hit rate – a considerably larger margin than the 1PP average improvement of the MMMNL model in the other four cases. A similar pattern holds for the comparison of the MEAA and the MMNL models.

Furthermore, the models accounting for ANA are superior both in- and out-of-sample in categories we have classified as low-risk/stake, except for Parties, where the MMNL outperforms the MEAA model. For categories of high-risk/stake, the ANA models outperform in cases of higher complexity (Cameras and Holiday destinations). It appears that understanding which attributes are, in fact, in the utility function is more critical for low-stake as well as high-stake and high-complexity settings. This result is in line with our expectations, as consumers may search for less information in low-stake settings (Laurent and Kapferer 1985) and simplify their decisions by ignoring attribute information in high-complexity settings (Payne et al. 1992).

3.3.3 Effects of Ignoring Preference Heterogeneity

To investigate possible biases due to ignoring preference heterogeneity while accommodating ANA, we compare the average attribute attendance probabilities, and the probability distribution of the number of attributes attended within the EAA and MEAA models computed based on Equation (3.11). These, along with corresponding confidence intervals, for both models are presented in Figure 3.2 and 3.3, respectively.[13]

First, from Figure 3.2, it is apparent that across all datasets, none of the attributes has exactly 0 % or 100 % attendance probability. This is in line with finding in Yegoryan et al. (2020) but in contrast to the results in Hess et al. (2013) and Hole et al. (2013). We observe some attributes with tiny attendance probabilities for more complex decisions (e.g., in Electric kettles and Holiday destinations datasets). Moreover, similar attributes (e.g., price or brand) in different applications have somewhat different attendance probabilities (i.e., they are application-specific). However, in most of the applications, price is one of the attributes with the highest attendance probabilities (50% or more according to the MEAA model).

Second, in line with previous literature (e.g., Hess et al. 2013, Hole et al. 2013, Yegoryan et al. 2020), ignoring preference heterogeneity results in a downward bias of attribute attendance probabilities. On average, the difference in attribute attendance probabilities between the MEAA and the EAA models across all datasets is 18.25PP ($p < 0.001$). However, in some cases, we do not observe a significant difference in particular attribute attendance probabilities between the two models (illustrated by very close mean values and overlapping confidence intervals). For example, the latter holds for all attributes but the price in the Video-streaming services dataset, or for three attributes (brand, capacity, and power) in the Electric kettles dataset. Nevertheless, in contrast to Hess et al. (2013) and Hole et al. (2013) (applications in the context of route and prescription medication choice, respectively), and, in line with Yegoryan et al. (2020) (application in the context of laptop and coffee-makers choice), in neither of our ten applications does ANA completely diminish after accounting for preference heterogeneity.

Also, the downward bias in the attribute attendance probabilities results in a shift of the probability distribution of the number of attributes attended to the right when we account for preference heterogeneity (see Figure 3.3). The only two cases where we do not observe such a shift are in the datasets of Video-streaming services and Electric kettles. On average, the mode of the distribution increases from the EAA to the MEAA model by 1.1 ($p < 0.01$), and the ratio of the average

[13] We have used parametric bootstrapping using 10.000 draws to generate the average attribute attendance and the average probability of attending a certain number of attributes based on the asymptotic distribution of class parameters $\hat{\gamma}$ presented in Appendix A.

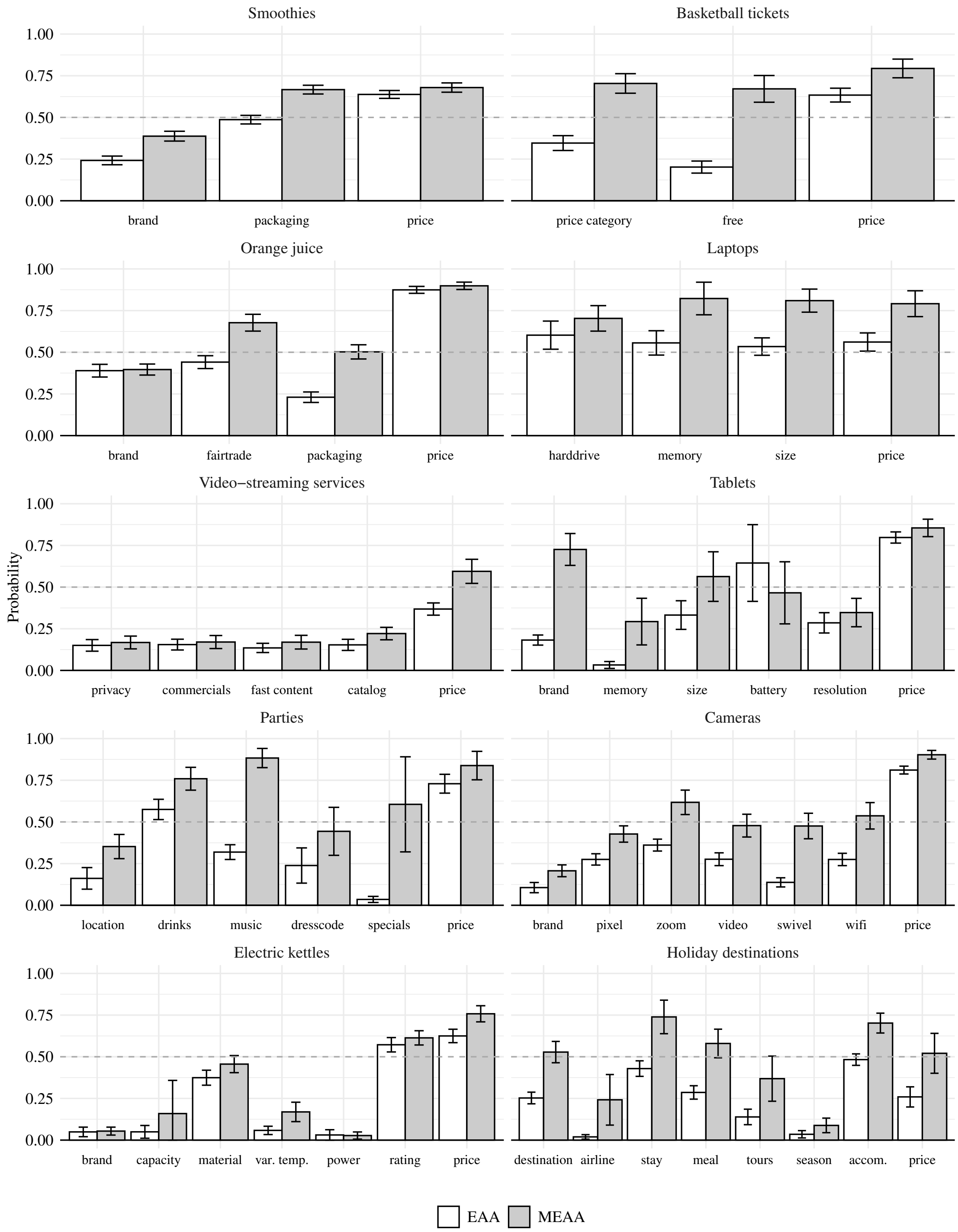


Figure 3.2. Average attribute attendance probabilities

number of attributes considered to the number of available attributes increases by 18.45PP ($p < 0.01$) across all datasets.

As we have established that not accounting for preference heterogeneity results in biases in the amount of identified attribute non-attendance, we focus on the results of the MEAA model. Several critical observations can be made from Figure 3.3. First, across all datasets, only a very small proportion of respondents relies on

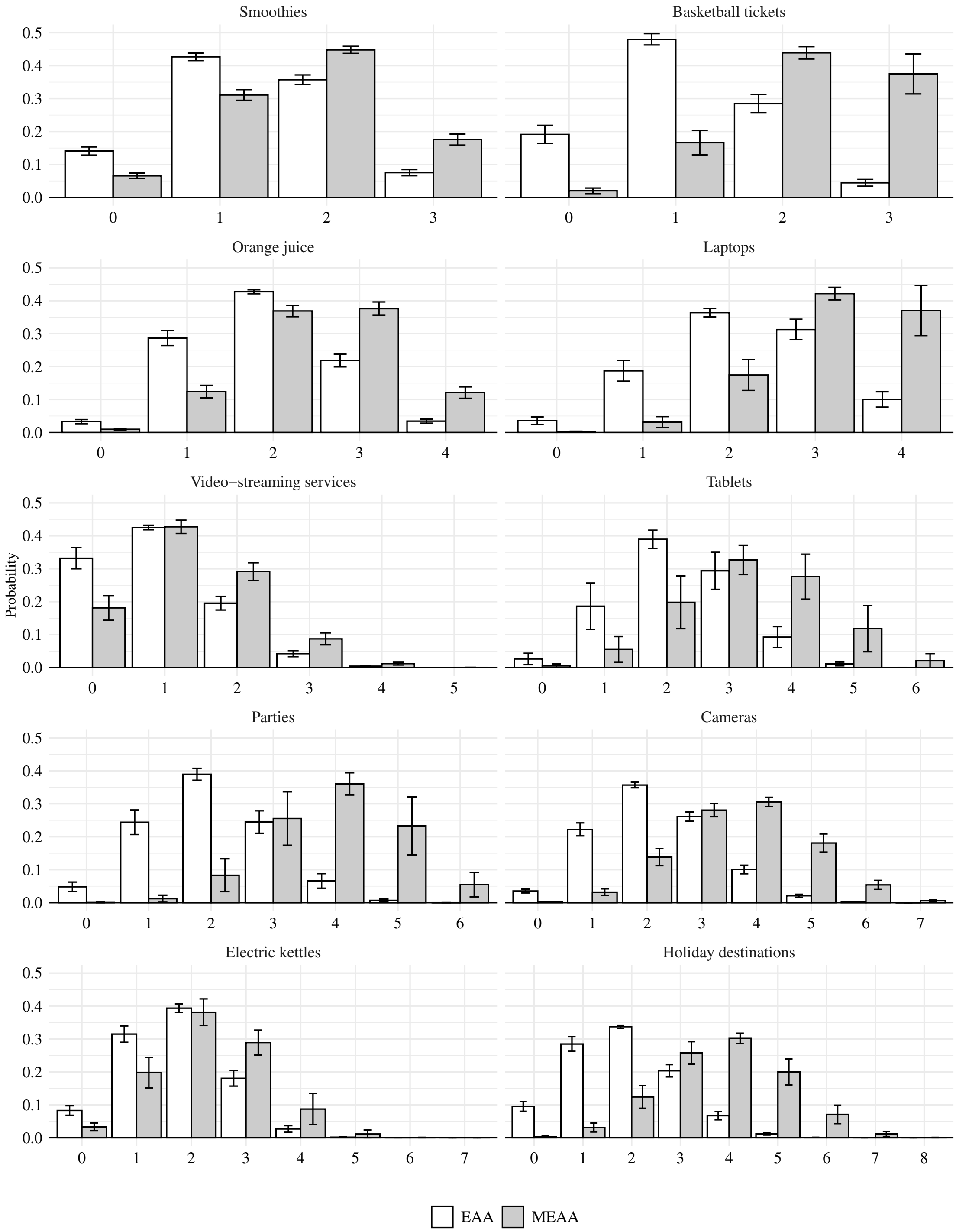


Figure 3.3. Probability of attending a certain number of attributes

random choice. The only exception is the Video-streaming services dataset, where we see around 18.13% probability of a random choice. Second, a much larger share of respondents incorporates all the available attributes in the decision in datasets of low versus high complexity (average of 28.88% vs. 3.69%). We also see that the proportion of respondents incorporating all attributes into the decision-making is substantially higher for the low complexity and high-risk/stake categories (average of 37.26% across the datasets of Basketball tickets and Laptops) vs. low complexity and low-risk/stake categories (average of 12.12% across the datasets of Smoothies and Orange juice). However, we do not observe a substantial difference when we consider the high-complexity settings.

Second, the average ratio of the number of attributes attended to the number of the available attributes substantially decreases in the high complexity settings (average difference of 70.78% vs. 47.75%, $p < 0.05$). On average, this ratio is also higher in high-risk/stake settings (60.26% vs. 46.25%). However, the difference in means is not statistically significant. The latter is mainly driven by the Parties dataset, for which the MMNL was the best fitting model and for which the preference heterogeneity potentially plays a more critical role. We can observe this descriptively in the probability distributions of the number of attributes attended in Figure 3.3.

Third, a slightly larger proportion of respondents tends to use lexicographic rule (i.e., consider only one attribute) in low- vs. high-risk/stake settings (right vs. left panel in Figure 3.3). The probability of attending only one attribute is particularly high in the Video-streaming services (42.73%) and Smoothies (31.11%) datasets, followed by the Electric kettles (19.77%), Basketball tickets (16.61%), and Orange juice (12.42%). For the rest of the datasets, the probability of attending only one attribute ranges between 1-5%.

3.3.4 Effects of Ignoring Attribute Non-attendance

Next, we turn to the de facto standard situation in current marketing literature when preference heterogeneity is accounted for while the analyst ignores ANA. To understand the potential consequences of ignoring ANA, we compare the mean and the standard deviation of the preference parameters implied by the MMNL and the MEAA model. Due do differing fit, and therefore, differing scales, we cannot directly compare the estimates of these models (Huber and Train 2001). To circumvent this issue, we regress the individual-level conditional estimates in the MEAA model on those of the (M)MMNL model (e.g., Frischknecht et al. 2014) and use the slope parameter as a rescaling factor (for details see Appendix B), which we apply for both population- and individual-level estimates.

First, we seek to examine the potential biases that may arise due to ignoring ANA on the population level. Here, we only compare the MEAA and the MMNL models, as the first moments of the MMMNL distribution are not informative in such comparison.[14] In particular, we check in how many cases we encounter biases in our hypothesized direction. Recall, we hypothesized that the direction of the bias would depend on the share of ANA and the true preference distribution. We

[14] We will include a comparison with the MMMNL model when we examine the distribution of individual-level conditional estimates.

expect that failing to accommodate ANA, contingent upon ANA occurring (i.e., a share of respondents ignoring some attributes in the decision-making) would bias 1) the mean estimate of the preference distribution towards zero regardless of the characteristics of the true distribution, 2) the estimated variance (or standard deviation) upwards when the true distribution lies further away from zero, leading to an overestimation of the amount of preference heterogeneity in the population, 3) bias the estimated variance (or standard deviation) downwards when the true distribution includes zero (i.e., spans on both positive and negative domains), leading to an underestimation of the amount of preference heterogeneity in the population.

While we do not know the true preference distribution in the population, we acknowledge that the MEAA model, which accounts for both preference heterogeneity and ANA, outperforms the MMNL model in the majority of the empirical applications (see section 3.3.2). Subsequently, we treat the results of the MEAA model to be closer to the truth and use it as a benchmark. To understand the direction of the bias in the variance (or standard deviation), we use the estimates of the mean and the standard deviation of the MEAA model to classify where the zero lies with respect to the implied preference distribution: within first and third quartiles, between the quartiles and the whiskers, or outside the whiskers[15] (for a simulated example see Figure 3.4).

We summarize the frequency and the percentage of occurrence of each of the expected biases in Table 3.4[16]. In the majority of cases, we do indeed see that the mean preference parameters in the MMNL are biased towards zero (column 2 in Table 3.4), which is very much in line with the previous findings (e.g., Collins 2012). There are only a few exceptions to this rule across our empirical applications. Four occur when the zero lies within the first and third quartiles of the "true" (MEAA) distribution, and one – when the zero is between the quartiles and the whiskers. Notably, the amount of ANA in all the five cases is not too large: ranging from 11.67% - 32.87%, with an average of 23.87%. In comparison, for the rest of the cases, the amount of ANA ranges from 9.70% - 97.23%, with an average of 50.09%.

Our results provide further support that ignoring ANA results in biased estimates of the mean of the preference distribution. While we cannot generalize, we do see some (descriptive) indication that not only the amount of ANA but also the location of the true preference distribution with respect to zero affect the magnitude of the bias in the mean. More specifically, the closer the true mean to zero, the lower the bias in the MMNL mean estimate.

[15]The whiskers are computed as the distance of 1.5 times the interquantile range above (below) of the upper (lower) quartile.

[16]The plots of the MEAA estimates against the MMNL estimates for each of the datasets are presented in Appendix C.

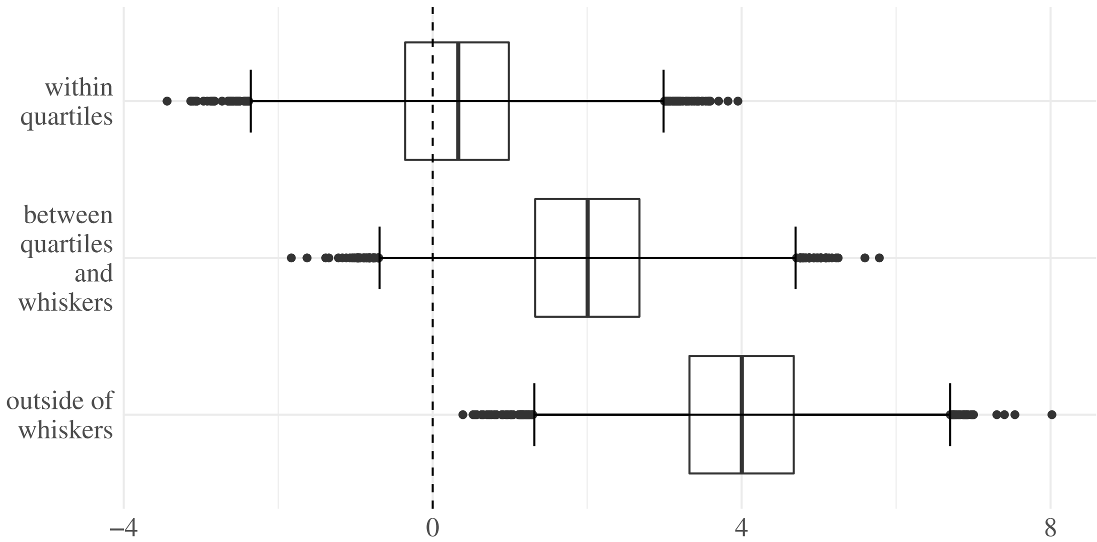


Figure 3.4. Classification of the location of the distribution with respect to zero

Regarding the bias in the variance, the results in Table 3.4 provide support for at least one of our hypothesized directions. In 100% of the cases where zero lies within the first and third quartiles, we see a downward bias in the standard deviations of preference distribution in the MMNL. The ANA probability varies in these cases from 11.67%-91.18%, with an average of 49.77%. If the zero lies outside of quartiles (rows 5 and 6 in Table 3.4), the results are split. For 19 out of 57 parameters (33.33% of cases), the estimates of the standard deviation in the MMNL have an upward bias (compared to the MEAA model results). These cases are consistent with our expected direction of the bias. However, for most of the parameters (66.67%), we observe a downward bias in the MMNL estimates of the standard deviation.

Parameter	In MEAA, 0 lies...	Downward bias (|MMNL| < |MEAA|)	Upward bias (|MMNL| > |MEAA|)
Mean	...within quartiles	23 (85.19%)	4 (14.81%)
	...between quartiles and whiskers	41 (97.62%)	1 (2.38%)
	...outside of whiskers	15 (100.00%)	0 (0.00%)
SD	...within quartiles	27 (100.00%)	0 (0.00%)
	...between quartiles and whiskers	29 (69.05%)	13 (30.95%)
	...outside of whiskers	9 (60.00%)	6 (40.00%)

Table 3.4. Frequency and the direction of biases when ignoring attribute non-attendance

To better understand the various patterns we observe in the population-level estimates, we now turn to examine the distribution of the individual-level estimates across different models. This is particularly helpful in understanding the differences in the uncovered preference patterns across the models (Keane and Wasi 2013). As we are more specifically interested in understanding the different cases of under- and overestimation of the preference heterogeneity when ignoring ANA, we plot the distribution of the individual-level estimates for selected cases in Figure 3.5. In addition to the MMNL and the MEAA models, we also include the MMMNL results[17].

All three attributes presented on the left panel have a relatively higher share of ANA (as identified by the MEAA model) relative to those presented on the right panel. The upper panel contains continuous attributes, which is the price in all ten applications. While, economically speaking, all else being equal, consumers should prefer lower prices, in the two presented cases in the upper panel of Figure 3.5, we observe some individuals with a positive price coefficient in the MMNL and the MMMNL models. This is a common problem that can arise for several reasons, including design errors in the CBC study, use of price as a proxy for quality, or due to normality assumption coupled with only limited data available for each individual (Allenby et al. 2014). One possible way to circumvent the issue is to impose sign constraints (Allenby et al. 2014). By contrast, instances of positive price coefficients are either completely diminished or substantially reduces in the MEAA model. This is a general pattern across our applications. More specifically, the MMNL and the MMMNL produce positive price coefficients in 9 out of 10, while the MEAA only in 5 datasets. On average, 6.94% and 7.78% of the sample have a positive price coefficient in the MMNL and the MMMNL models, respectively, compared to only 1.07% in the MEAA model. Hence, some of the resulting positive price coefficients in models accounting only for preference heterogeneity (MMNL and MMMNL) may be driven by people simply ignoring price when making choices in CBC settings. The MEAA model identifies, on average, 32% and 10% probability of ignoring price in the datasets of Smoothies and Cameras presented in Figure 3.5. In both cases, the disregard of ANA results in an overestimation of the amount of heterogeneity in the MMNL and the MMMNL models. We also observe a more substantial difference in the range of the distribution between the MEAA and the (M)MMNL models in Smoothies vs. Cameras. In the case of Smoothies, both ANA probability is higher, and the distribution is further away from the zero. Both factors may drive the magnitude of the bias.

The pattern of the distribution in the middle panel of Figure 3.5 is very similar to the one discussed above. However, here we present product features, which allow vertical differentiation. For such features, one could expect a clear direction

[17]Both the MMNL and the MMMNL estimates are rescaled. For details see Appendix B.

of preferences. For instance, in the case of video-streaming services, no rational consumer should prefer commercials to be shown (the left-hand middle panel in Figure 3.5). The MEAA model clearly identifies such a pattern. We find that a large proportion is indifferent: the average probability of ANA is 83%. The rest derives disutility from commercials.

The suggested pattern of preference distribution is different in the MMNL model. The large share of respondents that do not pay attention to this attribute has shifted the whole preference distribution towards zero. As a result, according to the MMNL model, we find people that have positive estimates, i.e., prefer commercials to be shown. Allowing for more flexibility also does not resolve the issue. The MMMNL fits two distributions: for one larger class tightly distributed around zero (with mean = -0.03 and sd = 0.27, see Table 3.7 in Appendix A) and another smaller class with a flatter distribution away from zero (with mean = -1.15 and sd = 1.33). As a result, we still see a substantial amount of individual estimates on the positive domain implying a preference for commercials to be shown.

This example is also a case where the MMNL estimate of the standard deviation exhibits a downward bias compared to the MEAA. However, the standard deviation estimated in the MEAA is not statistically significant (see Table 3.7 in Appendix A). As the amount of ANA increases, we lose precision in identifying the heterogeneity estimates (the mean estimate, however, is significant). We find other such examples across different features in our datasets. In particular, out of 9 cases where we observe that the zero lies further away from the distribution of the MEAA (outside of whiskers) and we find a downward bias in heterogeneity estimates in the MMNL (row 6 and column 3 in Table 3.4), six have an insignificant standard deviation estimate in the MEAA. In 27 out of 29 such cases where the zero lies between the quartiles and whiskers in the MEAA (row 5 and column 3 in Table 3.4), the estimates of standard deviation are, in fact, significant. Insignificant results, however, come along with a large share of ANA.

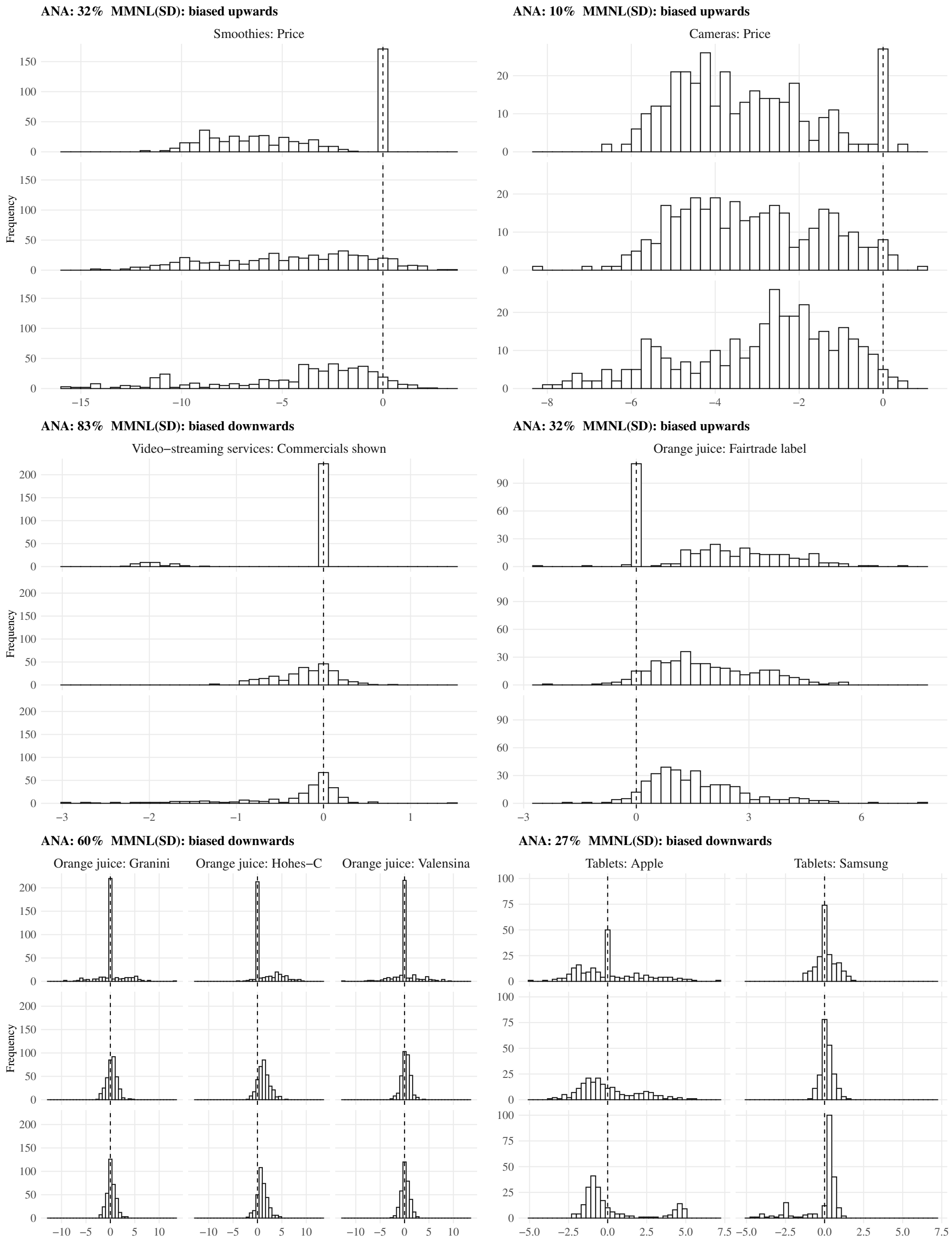
In contrast, in the case of the fairtrade label in the Orange juice dataset (the right-hand middle panel in Figure 3.5), where the ANA probability is much lower (average of 32%), and the distribution in the MEAA is somewhat closer to zero, we see a clear upward bias in the heterogeneity estimates in the MMNL. Both estimates of the mean and standard deviation in the MEAA model are significant (see Table 3.6 in Appendix A). Therefore, we offer two potential explanations of observing a downward bias in the MMNL estimates of the heterogeneity compared to the MEAA. First, as the amount of ANA increases and tends to 100%, the subsample based on which the mean and standard deviations in the MEAA are estimated shrinks. As a result, we lose precision and cannot read too much into the identified downward bias. Second, due to a smaller subsample, the MEAA may need to fit a much flatter distribution, necessitating much larger estimates of standard deviation.

Moreover, the Video-streaming dataset provides some interesting insights. It includes three (out of five) features of vertical differentiation, including commercials shown, privacy policy (not sharing any information, sharing usage information, or sharing usage and personal information), as well as fast content. For all these features, the MEAA model identifies a substantial amount of ANA (see Figure 3.2). We see similar patterns for all these features as for commercials shown presented in the left-hand middle panel in Figure 3.5. Hence, it comes as no surprise that not only the MEAA but also the EAA, which does not account for preference heterogeneity, outperforms the MMNL and the MMMNL models out-of-sample (see Table 3.3).

We now turn to discuss the uncovered preference patterns for features of horizontal differentiation, e.g., brand, which is included in many of our empirical applications. For such attributes, preference distribution may span both positive and negative domains or, following our classification, zero may be included within the quartiles. Recall that for these cases, we found that failing to accommodate ANA results in an underestimation of the amount of heterogeneity in preferences. We illustrate this in the lower panel of Figure 3.5.

Once again, we present an example with a substantially high amount of identified ANA on the left-hand panel: brand in Orange juice dataset with around 60% of ANA, and a lower amount – on the right-hand panel: brand in Tablets dataset with approximately 27% of ANA. In both cases, we obtain positive and negative partworth utilities for various brands in all models. Nevertheless, the preference distribution in the MMNL model is tighter compared to the MEAA model and much more so for brands in Orange juice than in Tablets datasets, which may be explained by many respondents ignoring the brand attribute in the former datasets. In the example of the Orange juice dataset (the left-hand lower panel in Figure 3.5), the MMMNL model does not necessarily perform better. In both classes, the implied distributions for brands do not differ much (see Table 3.6 in Appendix A). As a result, the preference distribution in the MMMNL model looks very much like one normal distribution.

We also find an underestimation of preference heterogeneity in the MMNL model for brands in Tablets dataset (the right-hand lower panel in Figure 3.5). However, as the ANA probability is much lower, the magnitude of the bias is also lower. In general, we see similar patterns in many other cases of attributes allowing horizontal differentiation, including additional features (free public transport, parking, or VIP parking) in Basketball tickets dataset, brand in Cameras and Smoothies, packaging in Orange juice and Smoothies, location, type of music, as well as specials in



Notes: The estimates of the MMNL and the MMMNL models are rescaled.

Figure 3.5. Parameter distribution of selected attributes for selected datasets

Parties, and catalog size (which included more TV or more movies content) in Video-streaming services.

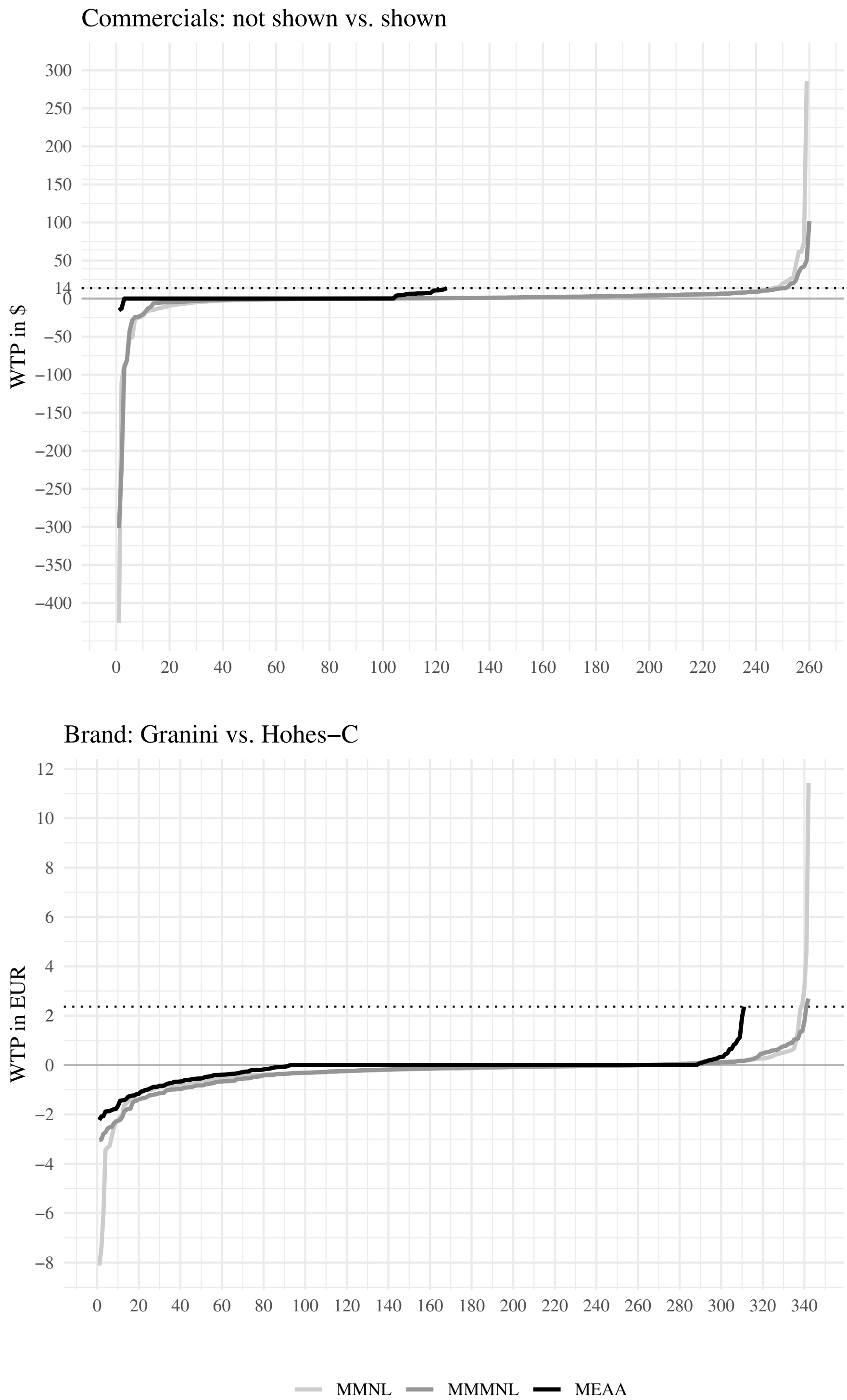
Unlike the example of the Orange juice datasets, though, the MMMNL model uncovers an interesting pattern in the example of the Tablet dataset (the right-hand lower panel in Figure 3.5). More specifically, the MMMNL model identifies two classes with distinct preferences leading to a bimodal distribution. In one class, respondents have a very high preference for Apple and are less price-sensitive. In the second class, they prefer other brands and are relatively more price-sensitive. There are no substantial differences between these two classes on other attributes (for details on parameter estimates, see Table 3.12 in Appendix A). The MEAA model cannot deal with such bimodality of preference distribution, as after disentangling the zeros, it still enforces a normal distribution on the rest of the sample. As a result, while the MEAA slightly outperforms the MMNL both in- and out-of-sample, it is inferior to the MMMNL (see Tables 3.2 and 3.3).

3.3.5 Managerial Implications

Overall, our analysis and detailed comparison of the different preference distributions implied by the models reveals that neglecting ANA in the model may result in considerable biases in the estimates. As a result, substantive decisions on optimal product design, market segmentation, demand estimation, (individual) pricing and targeting may be impaired.

To illustrate, in Figure 3.6, we present a comparison of individual-level WTP across the models for not showing commercials in the Video-streaming dataset and brand Granini vs. Hohes-C in the Orange juice dataset. For example, consider the potential decisions that can be made regarding offering consumers a video-streaming service with no commercials shown when ANA is neglected in the model. We find a larger mass with a positive valuation for this feature in the MMNL and the MMMNL models, i.e., the overall demand is considerably overstated in both these models (see the upper panel in Figure 3.6. Moreover, according to the MMNL and the MMMNL models, there is a share of consumers willing to pay more than \$14 (the upper bound of WTP in the MEAA model) for a video-streaming service with no commercials shown. Hence, it may still seem profitable to introduce the option. In contrast, the MEAA model suggests that there is a much lower demand for this feature, and respondents are not willing to pay more than \$14 for it. It is unclear whether the revenue that can be made from this limited number of consumers would cover the opportunity cost that could have been made by showing commercials.

Similarly, if a considerable share of consumers does not care about attributes that allow differentiating products horizontally (e.g., brands), the firm's pricing decisions may be impaired. For example, consider brand Granini vs. Hohes-C in the Orange juice dataset. We present the WTP distribution across models in the lower panel in Figure 3.6. The analyst neglecting ANA and basing decisions on the MMNL or MMMNL models again might overestimate the overall demand (larger mass with positive valuation compared to the MEAA model). Because of ANA, the average WTP in the MMNL and the MMMNL models is lower compared to the MEAA model (zeros excluded). This may lead to suboptimal pricing decisions and loss of potential profits for the firm.



Notes: One respondent with unrealistically high WTP in the MMNL model in the Video-streaming dataset has been dropped. Respondents with non-negative price coefficients are excluded.

Figure 3.6. Willingness-to-pay distribution for selected attributes

3.4 Conclusion

In this paper, we set out to 1) investigate the confounding between preference heterogeneity and ANA, 2) gain a deeper understanding of potential biases in uncovered preference distributions when either preference heterogeneity or ANA is neglected, and 3) examine the prevalence of ANA in a broader set of applications. The model comparison across ten empirical applications indicates that significant biases arise when preference heterogeneity or ANA is not accommodated. In particular, ignoring potential differences in individual preferences results in an overstatement of the amount of ANA. In the opposite case, not accounting for ANA leads to biases in preference estimates (both mean and variance). The magnitude of the bias depends on the location of the true preference distribution and the amount of ANA. We find that there is a higher likelihood of overestimating the amount of preference heterogeneity in the presence of ANA for attributes that allow firms to differentiate among products vertically. On the other hand, an underestimation of the preference heterogeneity can be expected for attributes that allow horizontal differentiation such as brands. Biases in the uncovered preference distribution lead to biases in demand estimation and may impair the firm's decisions on optimal product design, introductions of new products and features, segmentation and targeting, as well as pricing (e.g., Gilbride and Lenk 2010, Allenby and Ginter 1995).

Moreover, we find that explicitly accounting for ANA in choice models is critical in categories involving low risk/stakes as well as more complex settings that require consumers to make trade-offs on many attributes. As both factors may drive consumers to ignore attribute information when making choices, accommodating such behavior becomes critical. Notably, models that impose more flexible forms of preference heterogeneity cannot necessarily deal with existing ANA patterns in the data.

Several limitations of the existing approach for modeling both preference heterogeneity and ANA, namely the MEAA model, should be outlined. First, the MEAA model is not equipped to deal with multi-modal preference distribution. While it may sufficiently identify consumers that ignore the particular attribute, it still imposes one normal distribution for the rest of the sample. From this perspective, the MEAA and the MMMNL model seem to be complementary to each other. Future research could focus on further extensions of the MEAA model to allow for multi-modal distribution of preferences. Second, we have imposed the assumption of independence of attribute attendance in the models that account for ANA (EAA and MEAA). While this assumption is critical for retaining parsimony, it comes at a cost. More specifically, it does not allow for any correlation in the attribute attendance probabilities. On the other hand, relaxing this assumption results in a sharp increase in the number of parameters. Further research is necessary to find new approaches to accommodate this issue.

Another avenue for future research is to investigate the drivers of ANA. In our ten applications, we found that the risk/stakes and the complexity of the choice situation may lead to a higher ANA. It would be essential to understand how these factors affect consumers' attribute processing strategies. Furthermore, while we only looked at the risk/stakes of the decision, other facets of consumer involvement may affect the observed ANA patterns.

3.5 Appendix

3.5.1 Appendix A

In this Appendix, we present the estimation results of all the models for each of the ten datasets. Statistically significant estimates at a 5% significance level are indicated in bold. For all the datasets, we use dummy coding for the "none" option, linear coding for the price, and effect coding for other attributes. The omitted levels are indicated in a footnote of the corresponding table.

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility paramaters							
None	β	**-4.06** (0.07)	**-6.08** (0.12)	**-9.55** (0.30)	**-11.81** (0.47)	**-16.17** (0.84)	**-5.49** (0.35)
	σ			**5.87** (0.28)	**8.70** (0.35)	**6.73** (0.45)	**3.06** (0.25)
Brand:							
A	β	**0.30** (0.02)	**1.13** (0.10)	**0.55** (0.04)	**1.49** (0.15)	**0.20** (0.06)	**1.21** (0.11)
	σ			**0.68** (0.06)	**1.49** (0.13)	**0.28** (0.09)	**1.22** (0.11)
B	β	**-0.03** (0.03)	**-0.63** (0.10)	**-0.06** (0.04)	**-0.28** (0.11)	**0.40** (0.07)	**-0.49** (0.07)
	σ			**0.35** (0.06)	**1.28** (0.11)	**0.46** (0.07)	0.12 (0.20)
C	β	**0.06** (0.03)	**1.02** (0.09)	**0.06** (0.05)	**0.60** (0.16)	**-0.43** (0.07)	**0.84** (0.10)
	σ			**0.92** (0.06)	**2.78** (0.21)	**0.58** (0.08)	**1.37** (0.11)
Packaging:							
Glass bottle	β	**0.54** (0.02)	**1.50** (0.06)	**0.79** (0.05)	**1.74** (0.11)	**-0.06** (0.10)	**1.74** (0.10)
	σ			**0.85** (0.05)	**1.37** (0.10)	**0.75** (0.10)	**0.85** (0.07)
Tetrapak	β	**-0.79** (0.03)	**-2.09** (0.09)	**-1.30** (0.06)	**-2.50** (0.14)	**-0.62** (0.11)	**-2.34** (0.16)
	σ			**1.06** (0.07)	**1.57** (0.11)	**0.93** (0.11)	**1.23** (0.11)
Plastic cup	β	**-0.42** (0.03)	**-0.87** (0.07)	**-0.63** (0.05)	**-1.14** (0.10)	**-0.37** (0.08)	**-0.98** (0.11)
	σ			**0.87** (0.06)	**1.48** (0.09)	**0.80** (0.09)	**1.08** (0.10)
Price	β	**-2.02** (0.05)	**-4.07** (0.09)	**-3.83** (0.16)	**-6.25** (0.25)	**-7.23** (0.38)	**-2.06** (0.18)
	σ			**3.53** (0.14)	**3.09** (0.21)	**5.23** (0.34)	**1.84** (0.16)
Class paramaters							
Brand			**-1.15** (0.14)		**-0.46** (0.12)		
Packaging			-0.05 (0.10)		**0.69** (0.12)		
Price			**0.57** (0.10)		**0.75** (0.13)		
Class 2							0.03 (0.03)
LL		−7931.836	−6945.037	−6233.871	−5863.345		−5806.924
BIC		15935.457	13988.779	12611.311	11897.179		11909.960
No. parameters		(8)	(11)	(16)	(19)		(33)

Note: The omitted levels are Brand: D, Packaging: plastic bottle.

Table 3.5. Estimation results for the dataset: Smoothies

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility parameters							
None	β	**-3.63** (0.10)	**-5.12** (0.14)	**-8.23** (0.32)	**-9.31** (0.44)	**-18.13** (1.28)	**-3.12** (0.31)
	σ			**5.77** (0.33)	**5.95** (0.27)	**3.89** (0.39)	**2.81** (0.27)
Brand:							
Granini	β	**0.24** (0.06)	**1.28** (0.13)	**0.25** (0.10)	**1.10** (0.40)	**-0.08** (0.23)	**0.50** (0.17)
	σ			**1.35** (0.11)	**4.58** (0.53)	**1.52** (0.23)	**1.59** (0.16)
Hohes-C	β	**0.74** (0.05)	**2.58** (0.13)	**1.25** (0.11)	**3.13** (0.26)	**1.05** (0.22)	**1.44** (0.17)
	σ			**1.55** (0.11)	**3.16** (0.28)	**1.43** (0.21)	**2.09** (0.17)
Valensina	β	**0.23** (0.06)	**1.05** (0.13)	**0.24** (0.10)	0.31 (0.35)	0.01 (0.22)	0.24 (0.17)
	σ			**1.16** (0.11)	**4.13** (0.33)	**1.41** (0.26)	**1.57** (0.15)
Fairtrade label:							
Yes	β	**0.86** (0.04)	**2.20** (0.11)	**1.76** (0.10)	**2.67** (0.20)	**2.76** (0.28)	**1.46** (0.13)
	σ			**1.60** (0.11)	**1.73** (0.12)	**2.41** (0.21)	**1.42** (0.14)
Packaging:							
Carton	β	**0.38** (0.04)	**2.40** (0.15)	**0.78** (0.12)	**1.88** (0.25)	**1.20** (0.25)	**0.72** (0.18)
	σ			**2.07** (0.11)	**3.83** (0.27)	**2.42** (0.27)	**2.21** (0.15)
Price	β	**-2.69** (0.07)	**-4.05** (0.10)	**-5.06** (0.18)	**-6.50** (0.23)	**-12.22** (0.84)	**-2.49** (0.18)
	σ			**2.72** (0.15)	**2.35** (0.15)	**1.54** (0.20)	**0.87** (0.12)
Class parameters							
Brand			**-0.45** (0.16)		**-0.42** (0.14)		
Fairtrade label			-0.24 (0.16)		**0.75** (0.23)		
Packaging			**-1.22** (0.18)		0.01 (0.17)		
Price			**1.95** (0.19)		**2.20** (0.24)		
Class 2							**0.12** (0.04)
LL		−5083.525	−4575.238	−4049.225	−3880.148		−3836.181
BIC		10226.366	9243.689	8217.085	7912.826		7918.105
No. parameters		(7)	(11)	(14)	(18)		(29)

Notes: The omitted levels are Brand: Albi, Fairtrade label: No, Packaging: PET.

Table 3.6. Estimation results for the dataset: Orange juice

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility paramaters							
None	β	**-1.42** (0.12)	**-2.61** (0.19)	**-4.17** (0.37)	**-4.81** (0.52)	**-5.15** (0.63)	**-4.22** (0.85)
	σ			**3.07** (0.37)	**4.21** (0.52)	**3.98** (0.55)	**1.92** (0.45)
Privacy policy:							
Share usage	β	0.05 (0.03)	**0.67** (0.20)	**0.10** (0.04)	**1.07** (0.38)	0.07 (0.04)	0.30 (0.18)
	σ			0.11 (0.17)	0.36 (0.53)	0.11 (0.10)	**0.65** (0.19)
Share all	β	-0.19 (0.03)	**-2.19** (0.39)	**-0.27** (0.05)	**-3.04** (0.74)	-0.06 (0.05)	**-1.77** (0.31)
	σ			**0.47** (0.06)	**0.86** (0.86)	**0.20** (0.09)	**1.71** (0.29)
Commercials:							
Shown	β	**-0.11** (0.02)	**-1.36** (0.17)	**-0.17** (0.04)	**-1.81** (0.32)	-0.03 (0.04)	**-1.15** (0.22)
	σ			**0.40** (0.04)	0.60 (0.42)	**0.27** (0.06)	**1.33** (0.25)
Fast content:							
Yes	β	**0.20** (0.02)	**1.70** (0.23)	**0.24** (0.04)	**2.08** (0.56)	**0.11** (0.03)	**1.59** (0.29)
	σ			**0.36** (0.05)	**1.09** (0.33)	0.11 (0.09)	**1.83** (0.31)
Catalog size:							
More TV	β	**-0.11** (0.03)	**-1.70** (0.32)	-0.09 (0.05)	**-0.85** (0.40)	-0.06 (0.05)	-0.35 (0.25)
	σ			**0.33** (0.07)	**2.24** (0.40)	0.00 (0.28)	**2.53** (0.42)
More movies	β	**0.22** (0.03)	**1.69** (0.21)	**0.28** (0.04)	**2.00** (0.29)	**0.13** (0.05)	**1.64** (0.31)
	σ			**0.35** (0.06)	**0.54** (0.25)	0.12 (0.13)	**1.85** (0.33)
Price	β	**-0.08** (0.01)	**-0.38** (0.02)	**-0.13** (0.02)	**-0.30** (0.05)	**-0.09** (0.03)	**-0.53** (0.10)
	σ			**0.26** (0.02)	**0.39** (0.04)	**0.27** (0.03)	**0.28** (0.06)
Class parameters							
Privacy policy			**-1.76** (0.28)		**-1.63** (0.28)		
Commercials			**-1.72** (0.24)		**-1.61** (0.28)		
Fast content			**-1.88** (0.24)		**-1.62** (0.29)		
Catalog size			**-1.73** (0.25)		**-1.27** (0.22)		
Price			**-0.54** (0.16)		0.39 (0.31)		
Class 2							**-0.94** (0.06)
LL		−3591.151	−3278.248	−3264.935	−3167.175		−3161.749
BIC		7244.365	6657.350	6653.997	6497.266		6579.509
No. parameters		(8)	(13)	(16)	(21)		(33)

Notes: The omitted levels are Privacy policy: No sharing, Commercials: Not shown, Fast content: No, Catalog size: 5000 movies, 2500 TV episodes.

Table 3.7. Estimation results for the dataset: Video-streaming services

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility paramaters							
None	β	**-0.55** (0.07)	**-0.40** (0.08)	**-0.55** (0.16)	**-0.46** (0.18)	0.37 (0.71)	**-0.69** (0.18)
	σ			**1.61** (0.16)	**1.85** (0.20)	**9.07** (1.89)	**1.48** (0.18)
Location:							
Image	β	0.00 (0.07)	0.83 (0.43)	-0.06 (0.12)	0.42 (0.33)	**1.60** (0.62)	-0.19 (0.15)
	σ			0.33 (0.21)	0.80 (0.46)	**5.68** (1.26)	0.32 (0.24)
Cafe Madrid	β	**0.15** (0.07)	**1.36** (0.40)	**0.41** (0.12)	**1.87** (0.43)	**4.24** (1.00)	0.24 (0.15)
	σ			**0.41** (0.19)	**0.63** (0.32)	**2.23** (0.69)	0.25 (0.24)
B9	β	**-0.24** (0.08)	**-1.78** (0.67)	**-0.34** (0.12)	**-1.78** (0.46)	**-1.91** (0.79)	**-0.38** (0.15)
	σ			0.38 (0.32)	0.57 (0.72)	**3.19** (0.82)	0.28 (0.24)
Westbhf	β	**-0.19** (0.08)	**-1.72** (0.65)	**-0.31** (0.13)	**-1.27** (0.50)	**-4.36** (0.99)	-0.31 (0.16)
	σ			**0.57** (0.20)	**1.92** (0.57)	**3.57** (0.80)	**0.80** (0.24)
Apollo	β	0.13 (0.07)	0.31 (0.40)	**0.31** (0.13)	**0.82** (0.39)	**-2.72** (0.94)	**0.62** (0.15)
	σ			**0.78** (0.14)	**1.86** (0.43)	**8.73** (1.95)	**0.42** (0.21)
Drinks:							
Cheap prices	β	**0.63** (0.04)	**1.39** (0.13)	**1.17** (0.10)	**2.03** (0.23)	**2.57** (0.66)	**1.36** (0.13)
	σ			**1.02** (0.11)	**1.03** (0.18)	**4.68** (1.02)	**0.92** (0.14)
Normal prices	β	0.07 (0.05)	**0.27** (0.10)	**0.23** (0.07)	**0.35** (0.12)	-0.74 (0.44)	**0.33** (0.10)
	σ			**0.30** (0.13)	**0.45** (0.19)	**1.73** (0.52)	**0.51** (0.14)
Music:							
Mix	β	**0.28** (0.05)	**0.47** (0.15)	**0.80** (0.10)	**1.13** (0.16)	**2.47** (0.66)	**0.86** (0.12)
	σ			**0.44** (0.16)	**0.60** (0.20)	**4.61** (1.00)	**0.40** (0.18)
R&B/Hip hop	β	**-0.48** (0.06)	**-1.05** (0.23)	**-1.06** (0.16)	**-1.34** (0.24)	**-1.62** (0.73)	**-1.21** (0.17)
	σ			**1.65** (0.16)	**2.31** (0.28)	**11.76** (2.45)	**1.03** (0.19)
House	β	**0.36** (0.05)	**2.09** (0.19)	**0.60** (0.13)	**1.10** (0.23)	**6.50** (1.45)	**0.42** (0.17)
	σ			**1.59** (0.14)	**2.34** (0.28)	**10.69** (2.26)	**1.66** (0.20)
Dress code:							
No sneakers	β	**-0.18** (0.03)	**-0.90** (0.31)	**-0.33** (0.06)	**-0.90** (0.34)	-0.57 (0.30)	**-0.43** (0.08)
	σ			**0.47** (0.09)	**0.79** (0.19)	**1.84** (0.47)	**0.51** (0.11)
Specials:							
None	β	**-0.11** (0.05)	**2.32** (0.93)	-0.12 (0.07)	-0.23 (0.18)	**-2.19** (0.65)	-0.02 (0.09)
	σ			**0.39** (0.12)	**0.57** (0.27)	0.75 (0.46)	0.23 (0.17)
Happy hour	β	**0.17** (0.04)	**3.14** (1.03)	**0.24** (0.08)	0.50 (0.29)	**1.86** (0.54)	**0.26** (0.09)
	σ			**0.36** (0.12)	**0.91** (0.34)	**4.18** (0.87)	0.25 (0.14)
Price	β	**-0.17** (0.01)	**-0.31** (0.03)	**-0.31** (0.02)	**-0.45** (0.05)	**-0.35** (0.11)	**-0.39** (0.04)
	σ			**0.12** (0.03)	**0.16** (0.06)	**0.47** (0.12)	**0.18** (0.04)
Class paramaters							
Location			**-1.73** (0.48)		-0.62 (0.32)		
Drinks			0.31 (0.25)		**1.18** (0.38)		
Music			**-0.76** (0.20)		**2.14** (0.56)		
Dress code			**-1.24** (0.61)		-0.24 (0.64)		
Specials			**-3.44** (0.52)		0.65 (1.78)		
Price			**1.00** (0.29)		**1.79** (0.64)		
Class 2							**1.12** (0.07)
LL		−2016.365	−1924.861	−1771.785	−1750.117		−1713.113
BIC		4144.269	4005.879	3766.651	3767.931		3879.824
No. parameters		(15)	(21)	(30)	(36)		(61)

Notes: The omitted levels are Location: Abendrot, Drinks: expensive, Music: Rock/Alternative, Dress code: None, Specials: Go-go dancers.

Table 3.8. Estimation results for the dataset: Parties

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility parameters							
None	β	**-2.21** (0.09)	**-3.14** (0.13)	**-4.61** (0.29)	**-4.99** (0.45)	**-1.76** (0.40)	**-6.07** (0.52)
	σ			**2.32** (0.19)	**3.53** (0.32)	**1.50** (0.57)	**3.14** (0.34)
Brand:							
Ovente	β	-0.03 (0.04)	**-1.96** (0.54)	-0.12 (0.06)	**-3.50** (0.74)	-0.08 (0.14)	**-0.14** (0.07)
	σ			**0.34** (0.08)	0.01 (0.47)	0.18 (0.16)	**0.34** (0.09)
Hamilton Beach	β	-0.01 (0.04)	**1.28** (0.45)	0.05 (0.06)	**2.12** (0.53)	-0.01 (0.13)	0.11 (0.07)
	σ			**0.17** (0.07)	0.22 (0.35)	0.26 (0.24)	0.15 (0.11)
Capacity:							
1.2 liter	β	**-0.09** (0.04)	**-2.22** (0.68)	**-0.19** (0.06)	-2.24 (2.53)	**-0.30** (0.14)	**-0.14** (0.07)
	σ			**0.16** (0.08)	0.22 (1.04)	**0.42** (0.13)	0.16 (0.11)
1.5 liter	β	**0.07** (0.04)	**1.38** (0.55)	0.08 (0.06)	1.18 (1.69)	0.15 (0.12)	0.07 (0.07)
	σ			**0.16** (0.07)	0.59 (0.54)	0.13 (0.16)	0.07 (0.12)
Material:							
Glass	β	**0.27** (0.04)	**1.19** (0.12)	**0.62** (0.08)	**1.78** (0.30)	**1.97** (0.27)	**0.19** (0.07)
	σ			**0.87** (0.08)	**1.80** (0.29)	**2.94** (0.80)	0.06 (0.14)
Stainless steel	β	**0.28** (0.04)	**1.14** (0.12)	**0.51** (0.08)	**1.74** (0.29)	**2.39** (0.28)	**0.20** (0.08)
	σ			**0.83** (0.08)	**1.55** (0.22)	**1.59** (0.21)	**0.28** (0.09)
Variable temp.:							
Yes	β	**0.12** (0.03)	**2.17** (0.38)	**0.23** (0.05)	**1.28** (0.38)	**0.73** (0.14)	0.06 (0.05)
	σ			**0.37** (0.06)	**1.19** (0.30)	**0.93** (0.16)	0.16 (0.10)
Power:							
1100 Watts	β	-0.01 (0.03)	**-1.38** (0.44)	-0.02 (0.04)	**-2.26** (1.13)	0.08 (0.11)	-0.03 (0.05)
	σ			**0.16** (0.07)	**3.33** (0.99)	**0.45** (0.11)	0.14 (0.09)
Amazon rating:							
3 stars	β	**-0.84** (0.05)	**-2.60** (0.18)	**-1.70** (0.12)	**-3.68** (0.32)	**-1.59** (0.22)	**-1.95** (0.18)
	σ			**1.47** (0.12)	**0.76** (0.21)	**1.35** (0.22)	**1.41** (0.15)
4 stars	β	**0.11** (0.04)	**0.62** (0.09)	**0.33** (0.06)	**0.92** (0.14)	**0.31** (0.14)	**0.39** (0.07)
	σ			0.17 (0.09)	**0.48** (0.14)	**0.30** (0.14)	0.02 (0.28)
Price	β	**-0.30** (0.01)	**-0.77** (0.03)	**-0.53** (0.04)	**-1.00** (0.08)	**-0.53** (0.08)	**-0.72** (0.07)
	σ			**0.64** (0.05)	**0.51** (0.05)	**0.36** (0.06)	**0.56** (0.05)
Class parameters							
Brand			**-3.11** (0.60)		**-2.96** (0.45)		
Capacity			**-3.20** (0.75)		-2.53 (1.85)		
Material			**-0.52** (0.19)		-0.18 (0.21)		
Variable temp.			**-2.87** (0.44)		**-1.65** (0.42)		
Power			**-3.83** (0.91)		**-3.82** (0.75)		
Rating			0.29 (0.18)		**0.47** (0.18)		
Price			**0.52** (0.17)		**1.16** (0.26)		
Class 2							**0.58** (0.05)
LL		−2380.627	−1963.627	−1870.294	−1753.577		−1780.361
BIC		4854.121	4074.293	3926.323	3747.061		3939.930
No. parameters		(12)	(19)	(24)	(31)		(49)

Notes: The omitted levels are Brand: Cuisinart, Capacity: 1.7 liters, Material: Plastic, Variable temperature: No, Power: 1500 Watts, Amazon rating: 5 stars.

Table 3.9. Estimation results for the dataset: Electric kettles

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility Parameters							
None	β	**-2.45** (0.31)	**-5.63** (0.45)	**-5.52** (0.69)	**-6.31** (0.67)	**-6.63** (1.16)	**-4.89** (1.00)
	σ			**2.80** (0.54)	**1.82** (0.42)	**1.43** (0.37)	**1.92** (0.50)
Price category:							
Category 1	β	**0.5** (0.13)	**2.76** (0.23)	0.62 (0.35)	**1.33** (0.45)	-0.06 (0.50)	**1.02** (0.48)
	σ			**3.01** (0.43)	**4.20** (0.47)	**1.78** (0.34)	**3.20** (0.41)
Category 2	β	**0.14** (0.07)	**1.53** (0.19)	**0.60** (0.21)	**1.77** (0.34)	0.23 (0.43)	0.56 (0.33)
	σ			**1.93** (0.22)	**2.60** (0.37)	**2.34** (0.50)	**3.12** (0.44)
Category 3	β	**-0.31** (0.08)	**-1.16** (0.19)	**0.45** (0.15)	0.31 (0.27)	**0.60** (0.27)	0.00 (0.28)
	σ			**0.76** (0.17)	**1.62** (0.28)	**1.16** (0.30)	**0.70** (0.22)
Additional features:							
Free parking	β	**-0.23** (0.06)	**-8.35** (2.33)	**-0.83** (0.19)	**-1.26** (0.35)	**1.25** (0.41)	**-2.40** (0.36)
	σ			**1.77** (0.18)	**2.92** (0.38)	**1.40** (0.30)	**0.90** (0.30)
Free VIP	β	0.08 (0.06)	**2.99** (0.82)	0.26 (0.14)	0.29 (0.24)	**-0.67** (0.28)	**0.98** (0.22)
parking	σ			**1.28** (0.16)	**1.77** (0.29)	**1.17** (0.28)	**1.23** (0.24)
Free public	β	0.04 (0.06)	**3.01** (0.79)	**0.20** (0.10)	**0.43** (0.20)	**-0.68** (0.25)	**0.81** (0.19)
transport	σ			0.32 (0.20)	**1.04** (0.21)	**0.42** (0.25)	**0.50** (0.19)
Price	β	**-0.11** (0.02)	**-0.36** (0.03)	**-0.25** (0.03)	**-0.39** (0.04)	**-0.33** (0.06)	**-0.26** (0.05)
	σ			**0.15** (0.02)	**0.11** (0.02)	**0.12** (0.03)	**0.18** (0.03)
Class Parameters							
Price category			**-0.64** (0.20)		**0.88** (0.28)		
Additional features			**-1.39** (0.23)		0.73 (0.37)		
Price			**0.55** (0.18)		**1.38** (0.34)		
Class 2							**0.47** (0.10)
LL		−1959.438	−1561.666	−1370.051	−1350.408		−1303.796
BIC		3976.114	3202.033	2854.576	2836.755		2843.694
No. parameters		(8)	(11)	(16)	(19)		(33)

Notes: The omitted levels are Price category: 4, Additional feature: None.

Table 3.10. Estimation results for the dataset: Basketball tickets

		MNL	EAA	MMNL	MEAA	MMMNL Class 1	MMMNL Class 2
Utility parameters							
Hard drive:							
500GB	β	**-0.47** (0.05)	**-1.19** (0.15)	**-0.81** (0.11)	**-1.31** (0.16)	**-4.45** (1.94)	**-0.75** (0.12)
	σ			**0.66** (0.11)	0.31 (0.17)	**3.48** (1.39)	**0.56** (0.12)
750GB	β	0.03 (0.05)	0.08 (0.09)	0.06 (0.07)	0.08 (0.09)	**-1.04** (0.50)	0.15 (0.08)
	σ			0.01 (0.14)	0.17 (0.17)	1.66 (0.92)	0.03 (0.12)
Memory:							
4GB	β	**-0.71** (0.05)	**-1.77** (0.20)	**-1.22** (0.14)	**-1.66** (0.23)	**-8.51** (3.46)	**-1.04** (0.15)
	σ			**0.98** (0.12)	**1.00** (0.14)	**6.17** (2.48)	**0.82** (0.13)
6GB	β	**0.11** (0.05)	0.16 (0.10)	**0.21** (0.08)	**0.24** (0.10)	0.84 (0.54)	**0.20** (0.08)
	σ			**0.35** (0.11)	**0.35** (0.14)	**3.10** (1.44)	0.21 (0.14)
Dispaly size:							
12 inch	β	**-0.85** (0.06)	**-2.71** (0.21)	**-1.74** (0.17)	**-2.38** (0.30)	**-8.97** (3.74)	**-1.50** (0.20)
	σ			**1.39** (0.14)	**1.52** (0.19)	**7.32** (2.84)	**1.27** (0.18)
14 inch	β	**0.14** (0.05)	**0.59** (0.10)	**0.40** (0.09)	**0.56** (0.13)	**2.41** (1.14)	**0.37** (0.09)
	σ			**0.49** (0.09)	**0.58** (0.15)	**3.60** (1.34)	0.16 (0.16)
Price	β	**-0.79** (0.05)	**-2.12** (0.14)	**-1.51** (0.15)	**-2.02** (0.25)	**-2.42** (0.93)	**-1.72** (0.19)
	σ			**1.45** (0.16)	**1.56** (0.21)	**3.19** (1.23)	**1.31** (0.15)
Class parameters							
Hard drive			0.44 (0.36)		**0.89** (0.38)		
Memory			0.22 (0.30)		**1.68** (0.69)		
Display size			0.14 (0.21)		**1.51** (0.45)		
Price			0.25 (0.22)		**1.40** (0.47)		
Class 2							**1.06** (0.08)
LL		−1239.081	−1034.992	−992.023	−979.897		−969.003
BIC		2529.628	2150.861	2086.979	2092.137		2151.227
No. parameters		(7)	(11)	(14)	(18)		(29)

Notes: The omitted levels are Hard drive: 1 TB, Memory: 8 GB, Screen size: 15.6 inch.

Table 3.11. Estimation results for the dataset: Laptops

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility paramaters							
None	β	**-1.53** (0.07)	**-1.88** (0.09)	**-2.81** (0.22)	**-3.08** (0.26)	**-3.46** (0.25)	0.12 (0.71)
	σ			**2.40** (0.22)	**2.72** (0.26)	**2.29** (0.21)	**3.70** (1.00)
Brand:							
Apple	β	0.02 (0.04)	**2.92** (0.22)	0.12 (0.13)	0.18 (0.27)	**-0.93** (0.11)	**5.53** (1.18)
	σ			**1.75** (0.13)	**2.58** (0.35)	**1.01** (0.11)	**0.92** (0.40)
Samsung	β	0.00 (0.05)	**-1.00** (0.21)	**0.16** (0.08)	0.13 (0.13)	**0.51** (0.08)	**-3.40** (0.90)
	σ			**0.61** (0.11)	**1.01** (0.21)	**0.44** (0.12)	**2.02** (0.69)
Display size:							
7 inch	β	**-0.30** (0.03)	**-1.04** (0.19)	**-0.52** (0.06)	**-1.11** (0.31)	**-0.70** (0.08)	-0.29 (0.25)
	σ			**0.60** (0.08)	**0.80** (0.16)	**0.64** (0.08)	**0.87** (0.33)
Battery:							
7 hours	β	**-0.17** (0.03)	**-0.35** (0.13)	**-0.33** (0.05)	**-0.76** (0.30)	**-0.39** (0.06)	-0.18 (0.19)
	σ			**0.24** (0.10)	**0.44** (0.16)	**0.43** (0.08)	0.36 (0.24)
Resolution:							
1280×800px	β	**-0.20** (0.03)	**-1.07** (0.15)	**-0.37** (0.06)	**-1.49** (0.33)	**-0.42** (0.07)	**-0.41** (0.20)
	σ			**0.56** (0.07)	**0.75** (0.25)	**0.60** (0.08)	0.48 (0.27)
Storage capacity:							
16GB	β	**-0.24** (0.05)	**-5.93** (2.42)	**-0.37** (0.08)	-1.37 (0.73)	**-0.53** (0.10)	-0.39 (0.34)
	σ			**0.38** (0.13)	**1.02** (0.48)	**0.52** (0.14)	**1.37** (0.41)
32GB	β	**0.22** (0.04)	**3.11** (1.27)	**0.21** (0.06)	**0.48** (0.23)	**0.29** (0.08)	-0.13 (0.24)
	σ			0.11 (0.14)	0.59 (0.37)	0.21 (0.15)	0.14 (0.39)
Price	β	**-0.47** (0.02)	**-0.80** (0.03)	**-0.87** (0.05)	**-1.12** (0.08)	**-1.06** (0.07)	**-0.52** (0.17)
	σ			**0.49** (0.04)	**0.38** (0.08)	**0.54** (0.05)	**0.84** (0.20)
Class paramaters							
Brand			**-1.52** (0.20)		**1.04** (0.50)		
Size			-0.72 (0.40)		0.28 (0.66)		
Battery			0.78 (1.26)		-0.15 (0.87)		
Resolution			**-0.94** (0.30)		-0.65 (0.38)		
Storage capacity			**-3.56** (0.61)		-0.98 (0.74)		
Price			**1.38** (0.21)		**1.84** (0.43)		
Class 2							**-1.42** (0.06)
LL		−2414.468	−2142.529	−1952.786	−1926.379		−1846.543
BIC		4897.653	4399.588	4043.007	4036.004		3975.592
No. parameters		(9)	(15)	(18)	(24)		(37)

Notes: The omitted levels are Brand: Smarttab, Display size 10 inch, Battery: 11 hours, Resolution: 2560×1600px, Storage capacity: 64GB.

Table 3.12. Estimation results for the dataset: Tablets

		MNL	EAA	MMNL	MEAA	MMMNL Class 1	MMMNL Class 2
Utility parameters							
None	β	**-1.83** (0.06)	**-2.62** (0.08)	**-4.46** (0.19)	**-4.92** (0.27)	**-7.86** (0.52)	**-2.43** (0.23)
	σ			**3.50** (0.19)	**3.80** (0.27)	**4.54** (0.35)	**1.82** (0.17)
Brand:							
Sony	β	-0.04 (0.04)	**-1.20** (0.40)	-0.04 (0.05)	-0.13 (0.26)	0.02 (0.11)	-0.02 (0.08)
	σ			**0.44** (0.07)	**1.69** (0.23)	**0.73** (0.12)	**0.35** (0.14)
Nikon	β	**0.06** (0.03)	**1.54** (0.28)	0.11 (0.06)	**0.85** (0.28)	**0.39** (0.10)	-0.07 (0.08)
	σ			**0.58** (0.06)	**1.97** (0.24)	**0.88** (0.09)	**0.25** (0.11)
Panasonic	β	**-0.22** (0.04)	**-1.84** (0.32)	**-0.29** (0.05)	**-1.66** (0.34)	**-0.56** (0.12)	**-0.20** (0.08)
	σ			**0.28** (0.10)	**1.92** (0.28)	**1.07** (0.12)	0.16 (0.18)
Pixel:							
High	β	**0.38** (0.02)	**1.58** (0.11)	**0.60** (0.05)	**1.69** (0.17)	0.08 (0.06)	**1.18** (0.09)
	σ			**0.69** (0.05)	**0.86** (0.14)	**0.22** (0.08)	**0.85** (0.08)
Zoom:							
High	β	**0.42** (0.02)	**1.46** (0.09)	**0.68** (0.05)	**1.39** (0.15)	**0.20** (0.06)	**1.35** (0.09)
	σ			**0.71** (0.05)	**0.94** (0.12)	**0.23** (0.10)	**0.65** (0.07)
Video:							
Yes	β	**0.31** (0.02)	**1.27** (0.11)	**0.53** (0.04)	**1.25** (0.16)	**0.42** (0.07)	**0.73** (0.07)
	σ			**0.48** (0.05)	**0.54** (0.15)	**0.38** (0.10)	**0.65** (0.08)
Swivel:							
Yes	β	**0.17** (0.02)	**1.62** (0.17)	**0.25** (0.04)	**0.63** (0.13)	**0.19** (0.06)	**0.45** (0.08)
	σ			**0.49** (0.05)	**1.13** (0.15)	**0.46** (0.08)	**0.77** (0.09)
WiFi:							
Yes	β	**0.28** (0.02)	**1.29** (0.11)	**0.47** (0.04)	**1.06** (0.16)	**0.53** (0.08)	**0.57** (0.07)
	σ			**0.61** (0.06)	**0.94** (0.11)	**0.84** (0.11)	**0.61** (0.08)
Price	β	**-1.48** (0.03)	**-2.55** (0.06)	**-2.66** (0.11)	**-3.71** (0.17)	**-4.72** (0.35)	**-1.92** (0.12)
	σ			**1.80** (0.12)	**1.72** (0.14)	**2.49** (0.21)	**1.29** (0.10)
Class parameters							
Brand			**-2.17** (0.32)		**-1.36** (0.22)		
Pixel			**-0.97** (0.17)		-0.30 (0.20)		
Zoom			**-0.58** (0.16)		0.49 (0.32)		
Video			**-0.97** (0.19)		-0.09 (0.28)		
Swivel			**-1.86** (0.23)		-0.10 (0.32)		
WiFi			**-0.98** (0.19)		0.15 (0.33)		
Price			**1.46** (0.15)		**2.27** (0.30)		
Class 2							**0.08** (0.04)
LL		−5701.867	−4958.032	−4341.663	−4131.948		−4145.621
BIC		11488.175	10059.614	8852.210	8491.890		8637.455
No. parameters		(10)	(17)	(20)	(27)		(41)

Notes: The omitted levels are Brand: Canon, Pixels: Low, Zoom: Low, Video: No, Swivel: No, WiFi: No.

Table 3.13. Estimation results for the dataset: Cameras

		MNL	EAA	MMNL	MEAA	MMMNL	
						Class 1	Class 2
Utility parameters							
Destination:							
Overseas	β	**0.09** (0.02)	**1.64** (0.16)	**0.18** (0.08)	0.29 (0.22)	**-0.96** (0.43)	**0.22** (0.05)
	σ			**1.16** (0.08)	**2.39** (0.32)	**14.56** (4.26)	**0.48** (0.07)
Airline:							
Virgin	β	-0.01 (0.02)	**2.44** (1.06)	-0.03 (0.04)	-0.24 (0.33)	0.49 (0.26)	-0.07 (0.04)
	σ			**0.35** (0.05)	1.11 (0.57)	0.70 (0.36)	**0.38** (0.06)
Length of stay:							
12 days	β	**0.27** (0.02)	**1.21** (0.12)	**0.53** (0.05)	**0.94** (0.16)	**1.49** (0.45)	**0.53** (0.05)
	σ			**0.58** (0.06)	**0.70** (0.09)	**3.95** (1.14)	**0.36** (0.07)
Meal:							
Included	β	**0.26** (0.02)	**1.53** (0.18)	**0.53** (0.05)	**1.09** (0.18)	**1.22** (0.38)	**0.54** (0.05)
	σ			**0.47** (0.05)	**0.57** (0.11)	0.42 (0.31)	**0.48** (0.06)
Local tours:							
Available	β	**0.09** (0.02)	**1.16** (0.25)	**0.19** (0.04)	**0.70** (0.28)	-0.13 (0.31)	**0.20** (0.04)
	σ			**0.32** (0.06)	**0.53** (0.15)	**3.02** (0.92)	**0.25** (0.07)
Peak season:							
Peak	β	**0.04** (0.02)	**1.97** (0.60)	0.05 (0.04)	0.50 (0.46)	**0.90** (0.37)	0.02 (0.04)
	σ			**0.32** (0.06)	**2.00** (0.62)	**2.22** (0.65)	0.06 (0.11)
Accomodation:							
4-star	β	**0.43** (0.02)	**1.56** (0.10)	**0.87** (0.06)	**1.53** (0.16)	**2.10** (0.79)	**0.91** (0.07)
	σ			**0.79** (0.06)	**0.88** (0.11)	**2.26** (0.82)	**0.77** (0.07)
Price	β	**-0.17** (0.02)	**-1.00** (0.17)	**-0.33** (0.04)	**-0.76** (0.17)	0.01 (0.21)	**-0.39** (0.04)
	σ			**0.34** (0.05)	**0.44** (0.11)	0.11 (0.21)	**0.39** (0.06)
Class parameters							
Destination			**-1.09** (0.19)		0.12 (0.26)		
Airline			**-4.14** (0.65)		-1.35 (0.91)		
Length of stay			-0.29 (0.19)		**1.11** (0.54)		
Meal included			**-0.92** (0.20)		0.33 (0.36)		
Tours			**-1.87** (0.39)		-0.60 (0.63)		
Season			**-3.49** (0.63)		**-2.45** (0.54)		
Accommodation			-0.07 (0.14)		**0.87** (0.29)		
Price			**-1.07** (0.32)		0.09 (0.51)		
Class 2							**1.09** (0.04)
LL		−2686.871	−2395.588	−2262.399	−2172.046		−2160.810
BIC		5441.272	4926.234	4659.856	4546.680		4600.179
No. parameters		(8)	(16)	(16)	(24)		(33)

Notes: The omitted levels are Destination: Australia, Airline: Qantas, Length of stay: 7 days, Meal: Not included, Local tours: Not available, Peak season: Off-peak, Accomodation: 2-star

Table 3.14. Estimation results for the dataset: Holiday destinations

3.5.2 Appendix B

In this Appendix, we plot the individual-level estimates in the MEAA model against those in the MMNL and MMMNL model along with the results of the fitted linear regression of the form: $\beta_i^{\text{MEAA}} = a + b \cdot \beta_i^{\text{(M)MMNL}} + \epsilon_i$. The estimated slopes $\hat{b}$ serve as a rescaling coefficient for the (M)MMNL model, which we apply for both population- and individual-level estimates. For each, we report the estimates, R-squared, and the significance of the estimates. * denotes significance at 5%, ** – at 1%, and *** – at 0.1% significance level.

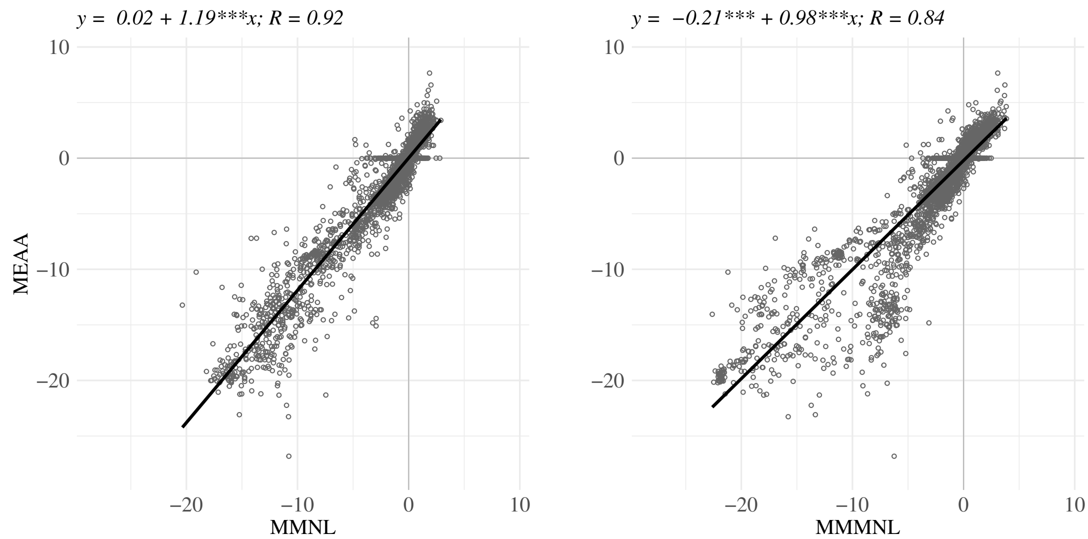


Figure 3.7. Individual-level estimates: Smoothies

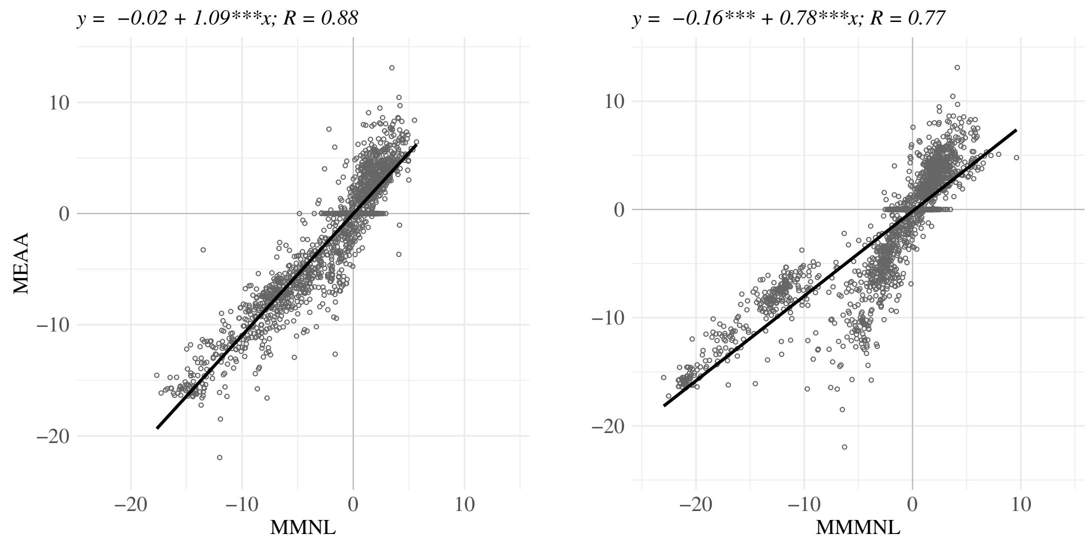


Figure 3.8. Individual-level estimates: Orange juice

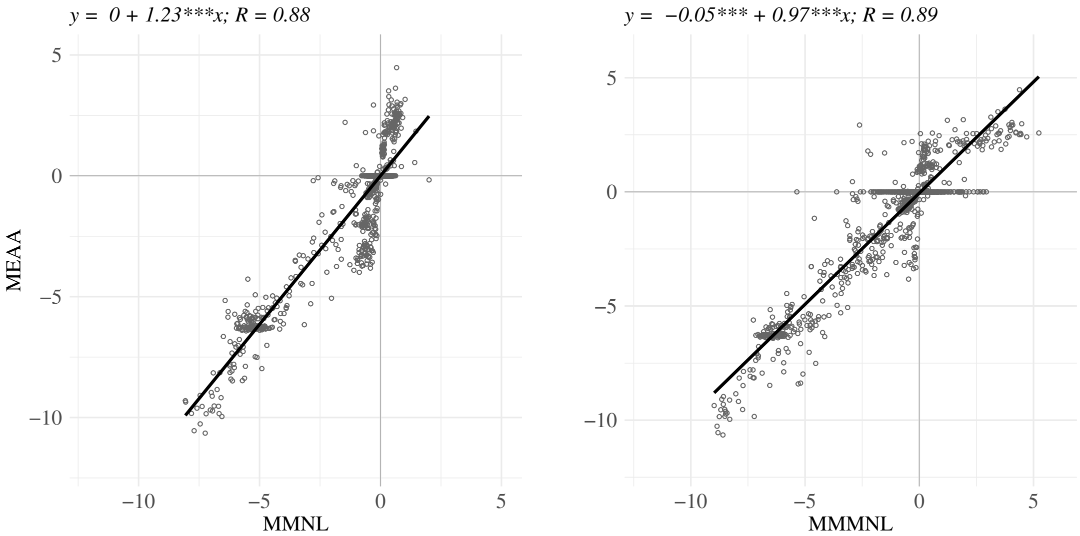


Figure 3.9. Individual-level estimates: Video-streaming services

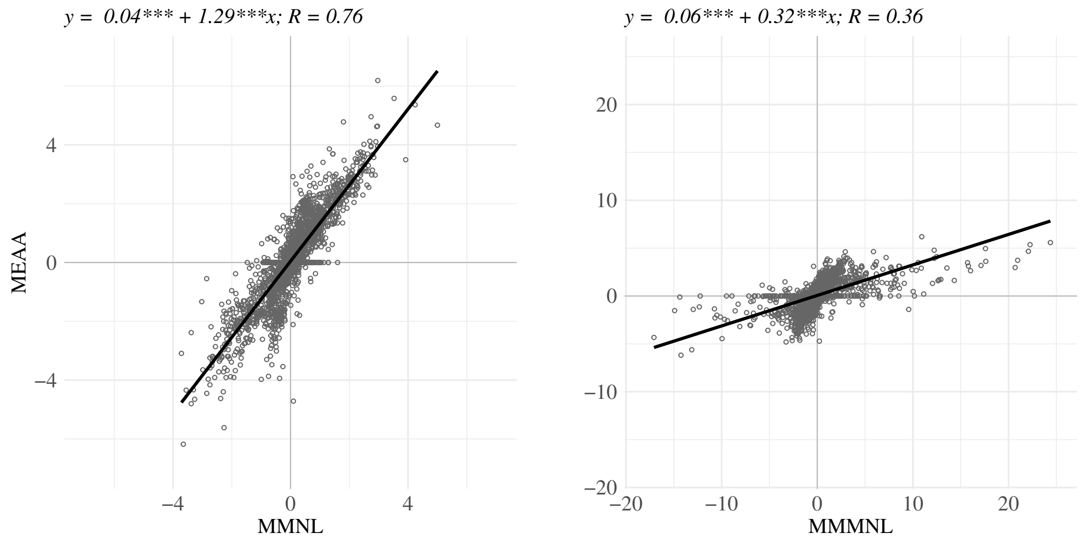


Figure 3.10. Individual-level estimates: Parties

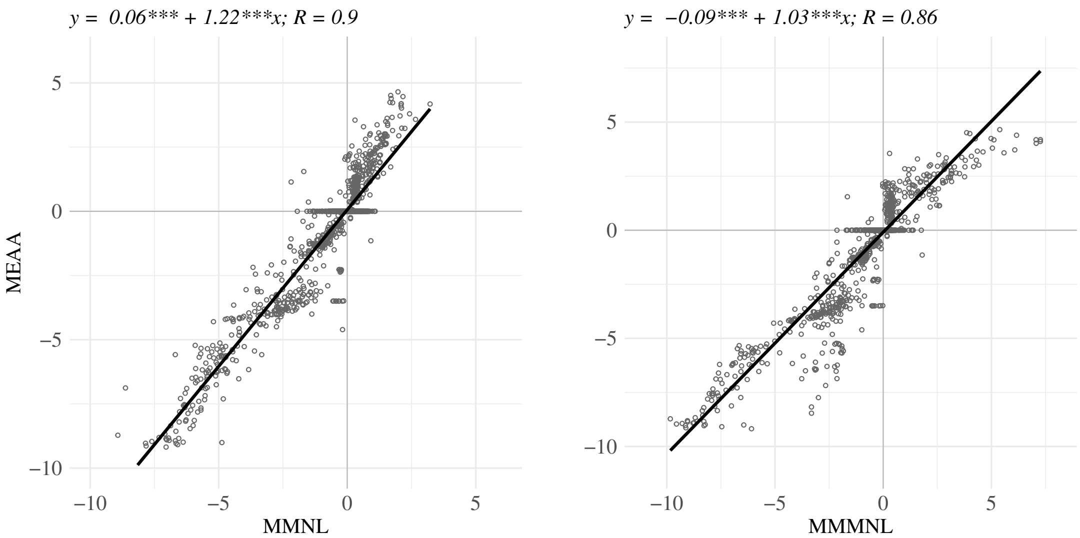


Figure 3.11. Individual-level estimates: Electric kettles

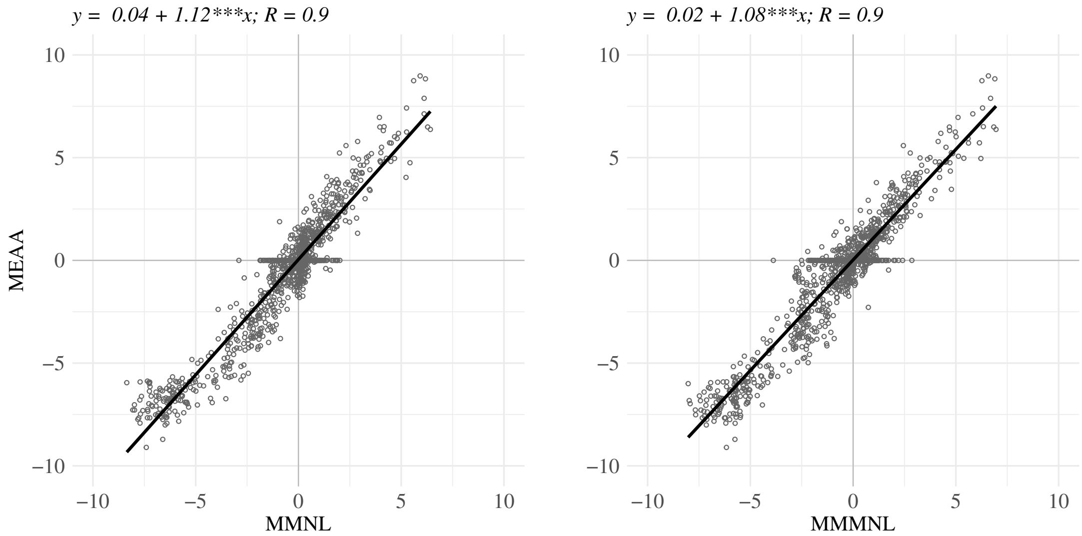


Figure 3.12. Individual-level estimates: Basketball tickets

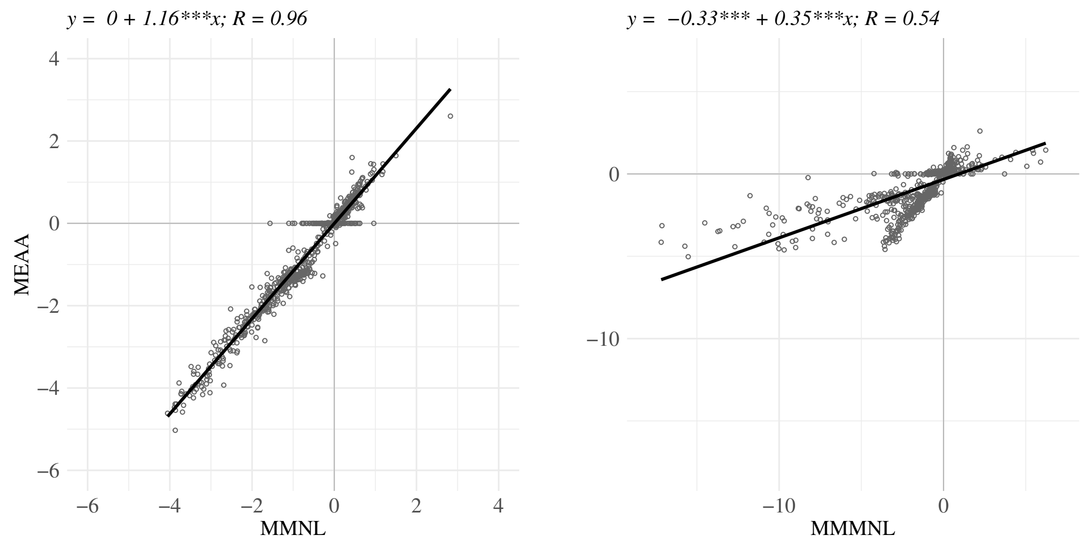


Figure 3.13. Individual-level estimates: Laptops

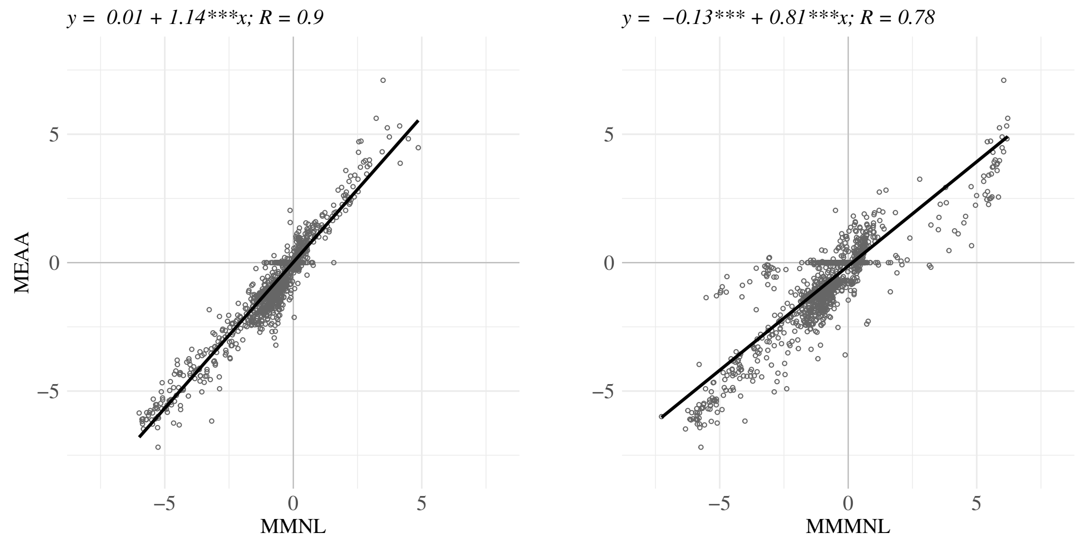


Figure 3.14. Individual-level estimates: Tablets

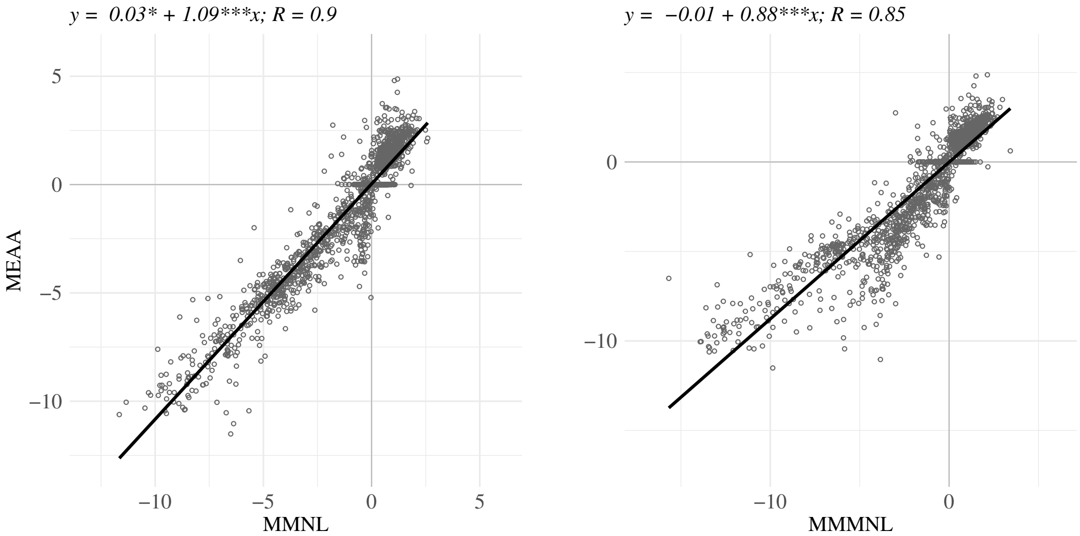


Figure 3.15. Individual-level estimates: Cameras

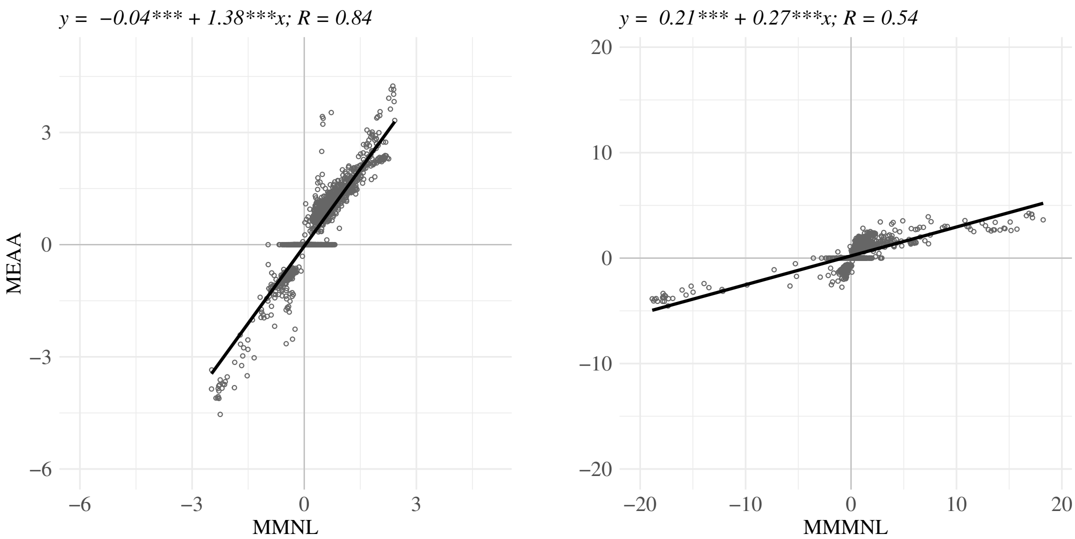


Figure 3.16. Individual-level estimates: Holiday destinations

3.5.3 Appendix C

In the following Appendix, we present scatterplots with the population-level estimates of the parameters for the MEAA and the MMNL models against each other. The MMNL estimates are rescaled using the slope parameters in Appendix B. The left panel plots the estimate of the mean and the right panel – the estimates of the standard deviation.

Colors of the dots represent where the zero lies in the MEAA model according to our classification: black - within quartiles, grey - between quartiles and whiskers, white - outside of whiskers.

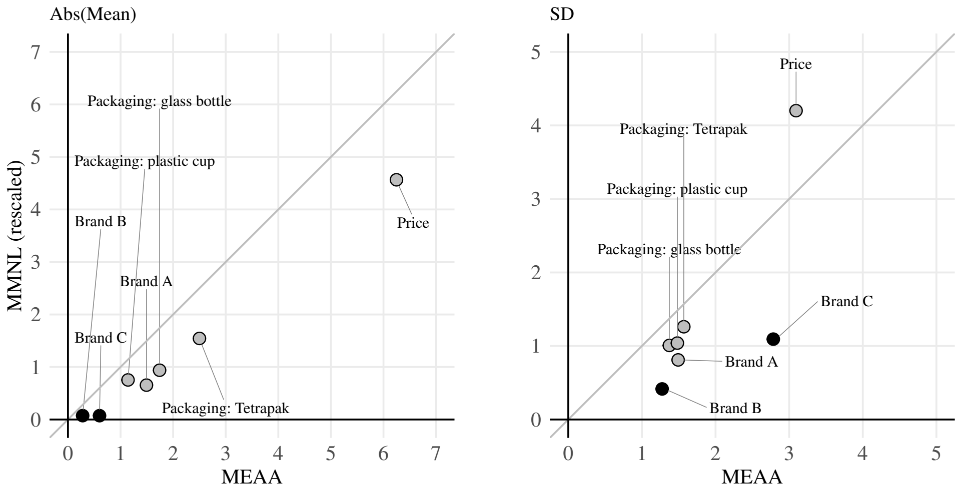


Figure 3.17. Population-level estimates: Smoothies

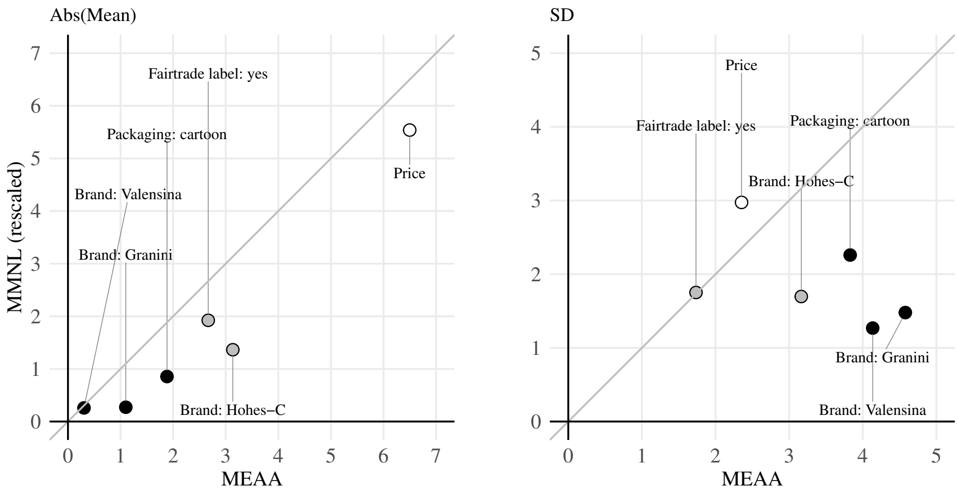


Figure 3.18. Population-level estimates: Orange juice

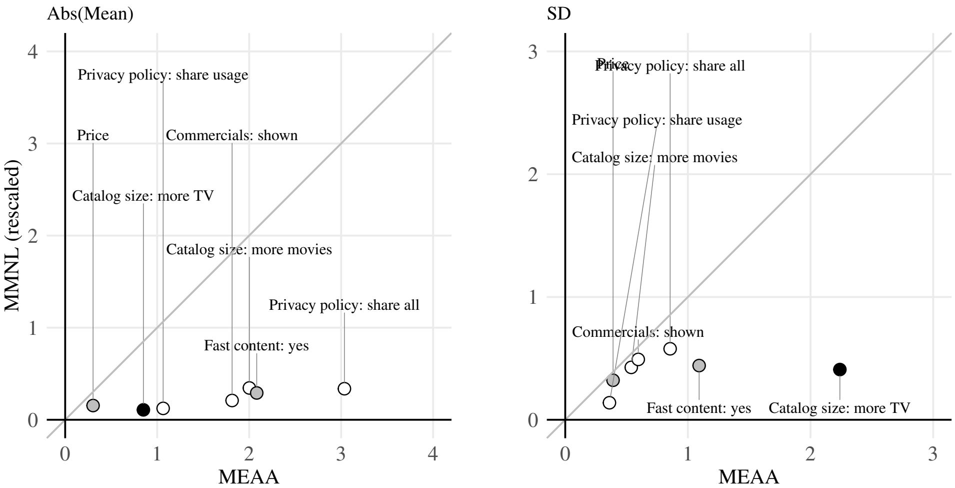


Figure 3.19. Population-level estimates: Video-streaming services

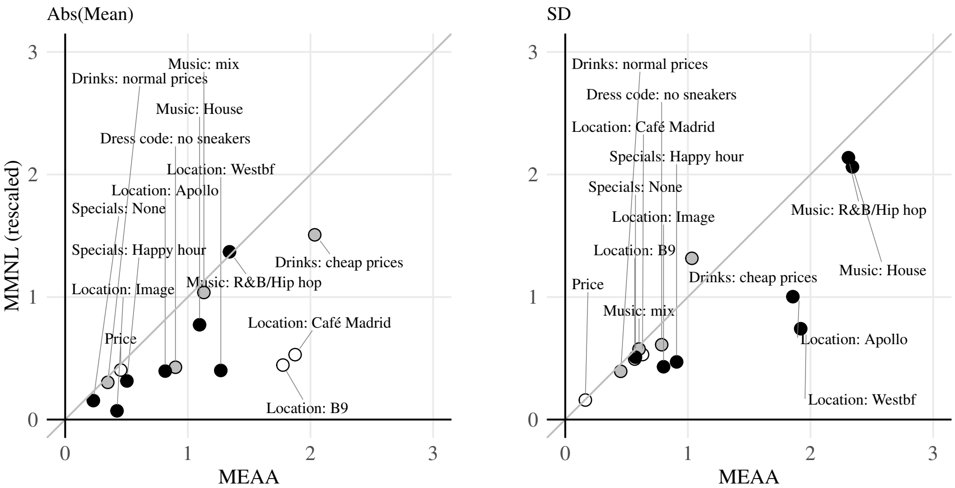


Figure 3.20. Population-level estimates: Parties

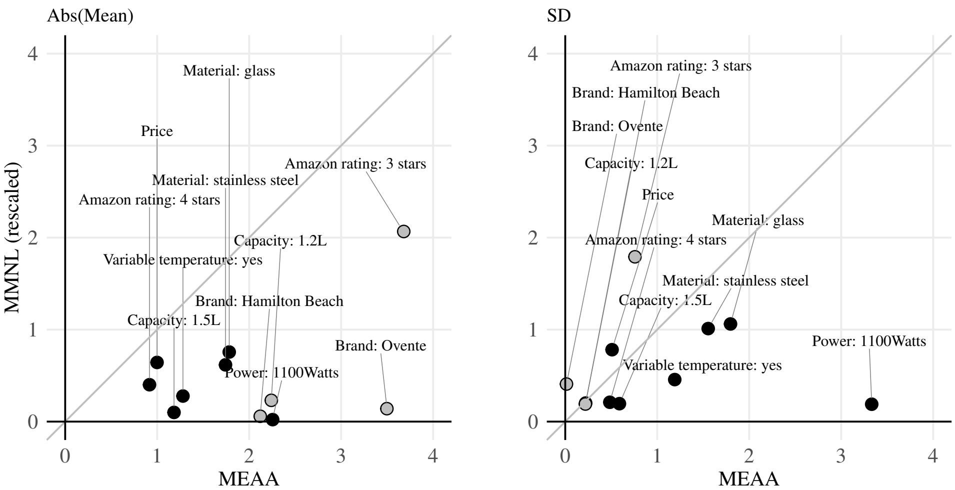


Figure 3.21. Population-level estimates: Electric kettles

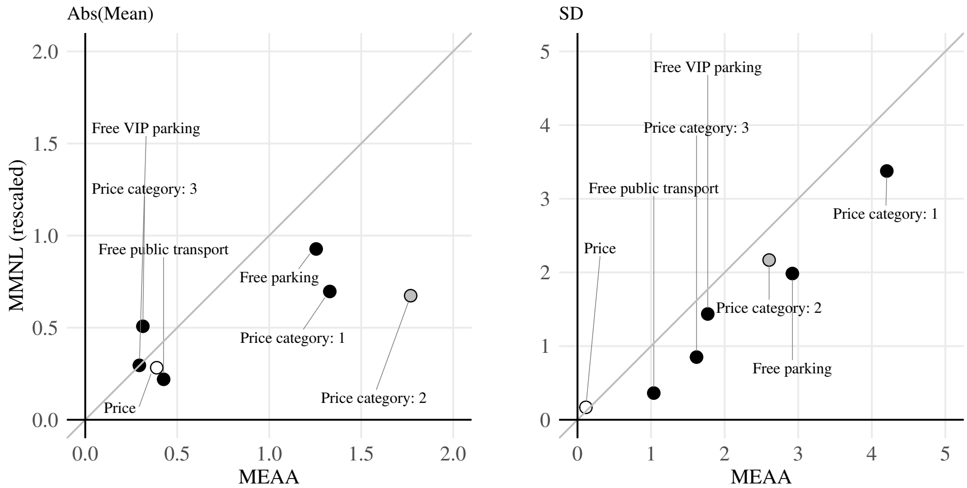


Figure 3.22. Population-level estimates: Basketball tickets

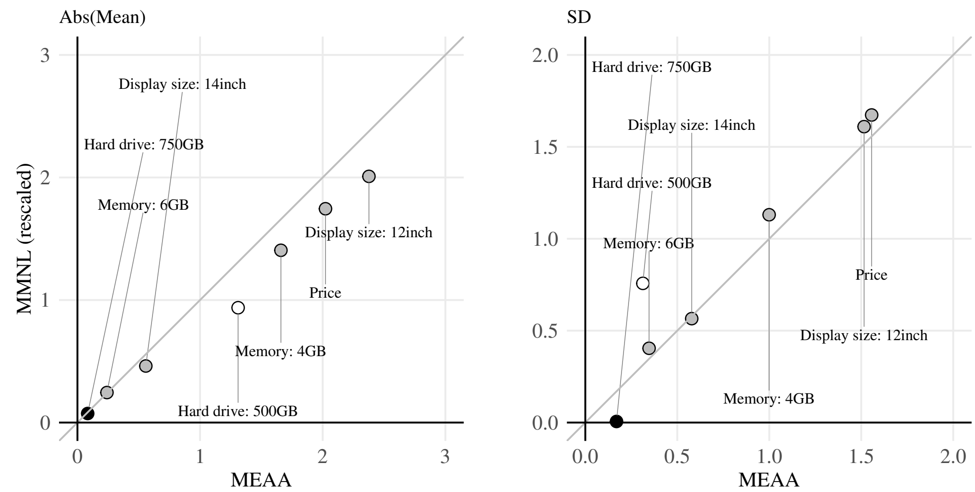


Figure 3.23. Population-level estimates: Laptops

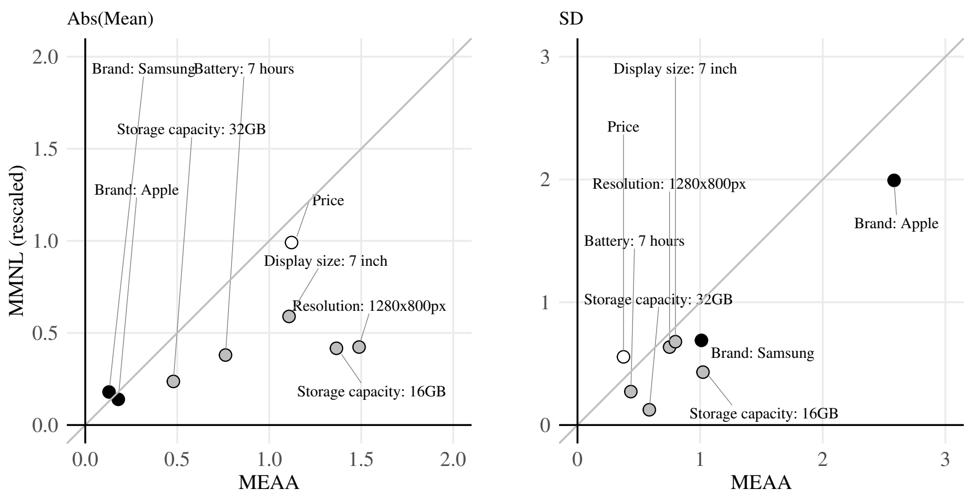


Figure 3.24. Population-level estimates: Tablets

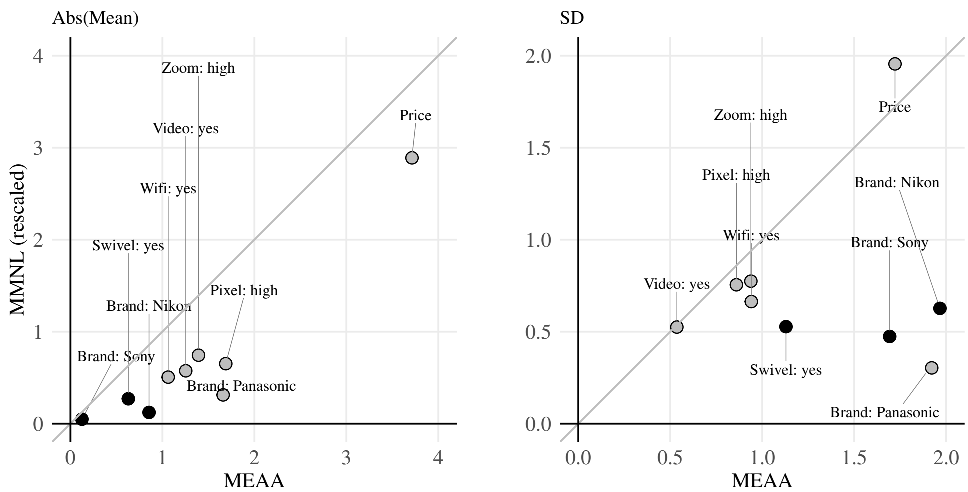


Figure 3.25. Population-level estimates: Cameras

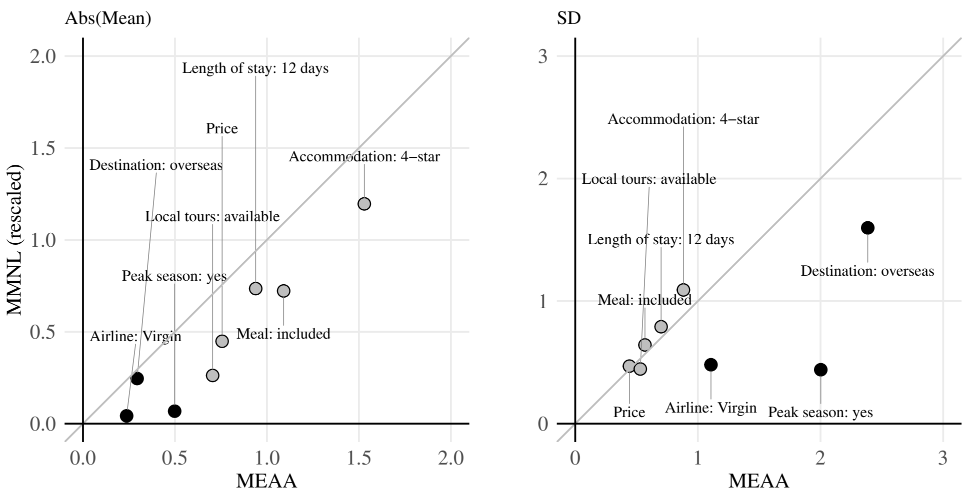


Figure 3.26. Population-level estimates: Holiday destinations

4 | Inferring Attribute Non-attendance using Eye Tracking in Choice-based Conjoint Analysis [1]

Narine Yegoryan, Daniel Guhl, Daniel Klapper

Abstract

Traditionally, choice-based conjoint analysis relies on the assumption of rational decision makers that use all available information. However, several studies suggest that people ignore some information when making choices. In this paper, we build upon recent developments in the choice literature and employ a latent class model that simultaneously allows for attribute non-attendance (ANA) and preference heterogeneity. In addition, we relate visual attention derived from eye tracking to the probability of ANA to test, understand, and validate ANA in a marketing context. In two empirical applications, we find that a) our proposed model fits the data best, b) the majority of respondents indeed ignore some attributes, which has implications for willingness-to-pay estimates, segmentation, and targeting, and c) even though the latent class model identifies ANA well without eye tracking information, our model with visual attention helps to better understand ANA and individual-level behavior.

Keywords

Attribute non-attendance, Eye tracking, Discrete choice modeling, Choice-based conjoint analysis

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[1] This chapter is published in Yegoryan, N., Guhl, D., and Klapper, D. (2020). Inferring Attribute Non-attendance using Eye Tracking in Choice-based Conjoint Analysis. *Journal of Business Research*, 111: 290–304. DOI: https://doi.org/10.1016/j.jbusres.2019.01.061.

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4.1 Introduction

Choice-based conjoint (CBC) analysis is a popular tool in marketing used to elicit consumer preferences, predict consumers' response to new product introductions, identify segments that similarly value product attributes, and optimize product design, targeting and pricing strategies (Rao 2014). The basis for analyzing the observed choices from CBC is the random utility maximization (RUM) model, with consumer "rationality" as its key behavioral pillar (McFadden 2001). More explicitly, under RUM, consumers are considered to have stable preferences, process all available information, and select the option that maximizes their utility. However, the validity of these assumptions has been widely challenged (e.g., DellaVigna 2009). In particul, with respect to the assumption of full information processing, it has long been argued that due to limited cognitive capacity, individuals often simplify their choices (e.g., Payne et al. 1992) and ignore some information about product attributes or alternatives (e.g., Orquin and Loose 2013).

The marketing literature has been mainly interested in the case where consumers neglect some of the available alternatives, which is conventionally labeled as "choice set" formation (e.g., Swait and Ben-Akiva 1987; Bronnenberg and Vanhonacker 1996). This issue is specifically common in revealed preference data (i.e., market data), where consumers face dozens or even hundreds of product options. In typical CBC settings, alternatives are usually restricted to a manageable number, e.g., three to four, and include a higher number of attributes (Rao 2014). However, some respondents may not deem all the attributes to be relevant or may tend to ignore them due to choice task characteristics, e.g., complexity (Hensher 2014). Hence, in CBC, it seems more plausible that respondents ignore attributes, conventionally termed "attribute non-attendance" (ANA)[2], rather than alternatives. In turn, in a given context, non-attended attributes do not contribute to the utility of a particular individual, implying that the corresponding preference parameters in the utility specification should be zero. In light of ANA, models assuming the use of all attributes in decision-making (hereafter "full (attribute) attendance"[3]) may result in biases in parameter estimates and, subsequently, in the derived willingness-to-pay (WTP) and welfare estimates (e.g., Gilbride et al. 2006; Scarpa et al. 2009). Given the plausibility and implications of ANA, in the following paper, we focus on its prevalence in a marketing context.

One of the most promising ideas for tackling ANA, mainly issuing from fields such as transportation, environmental, and health economics, is the use of a

[2] Note that the term "non-attendance" comes mainly from transportation science and in this context is used as a synonym for "ignoring" or "not considering" an attribute in the decision-making. To avoid being at odds with the main body of ANA literature, we adopt the corresponding terminology.

[3] Note that as we assume all alternatives are considered, "full (attribute) attendance" is equivalent to full information processing or full compensatory decision rule.

latent class model, where each a priori defined class represents a specific attribute attendance/non-attendance pattern (hereafter “attribute processing strategy”) and hence a different utility specification (e.g., Hole 2011; Hess et al. 2013). The main advantage of this approach is that ANA can be inferred based on the observed choices alone instead of relying on auxiliary information such as respondents' self-stated measures (e.g., Hensher 2006) or proxies of ANA derived from process tracing techniques (e.g., Currim et al. 2015; Meißner et al. 2011). Such information can still be useful, and using it to augment the models for inferring ANA is a promising strategy for obtaining a better understanding of the underlying individual behavior. For example, Hole et al. (2013) and Hess et al. (2013) demonstrate the benefits of using a stated ANA measure coupled with the latent class model. Nevertheless, an open question remains: how useful are process tracing measures, specifically eye tracking, within such a modeling framework for identifying ANA? This question is precisely the focus of the current paper.

We build on Hole et al. (2013) and use a latent class approach that allows for the simultaneous inference of ANA and preference heterogeneity and, in addition, integrates information from eye tracking. In doing so, our objective is to better understand and capture different attribute processing strategies individuals may apply when making choices. Measures derived from eye tracking, which are representative of underlying cognitive processes (Wedel and Pieters 2008) and indicate the relevance of information (Meißner and Oll 2017), are best suited for this purpose. Moreover, as Meißner et al. (2016) demonstrate, individuals become more efficient and selective in how they look at information during CBC tasks. Thus, eye tracking can be particularly informative in uncovering ANA in CBC. Furthermore, eye movements are driven by both top-down (e.g., consumers' goals, traits) and bottom-up (e.g., salience, location, features of the stimuli) factors (Wedel and Pieters 2008). As such, they may allow different drivers of ANA, i.e., person- (e.g., true irrelevance) and task-related (e.g., complexity), to be captured.

Our second objective is to understand the effect of visual attention on consumers' actions, i.e., choice. We model this relationship so that visual attention affects the likelihood of attending an attribute. Subsequently, the attended attributes enter the utility function, are traded-off against each other and affect choice. Additionally, we investigate whether this relationship varies across attributes.

Third, we aim to understand the prevalence of ANA in a marketing context, where typically we observe varying levels of task complexity (e.g., many product features and alternatives), consumer involvement, knowledge, and risks associated with the product category (e.g., buying a car involves higher stakes than buying a pen). Additionally, we aim to assess the consequences of neglecting ANA for managerially relevant measures, such as WTP.

In two empirical applications, we indeed find evidence that individuals ignore attributes, with the majority attending to only three to four out of six available and almost no one attending to all. We demonstrate that neglecting ANA results in substantial biases in preference parameters and, accordingly, in derived aggregate and individual-level measures such as the relative importance of attributes and WTP. Moreover, we find a positive and significant effect of visual attention on the likelihood of attending an attribute and demonstrate that eye tracking is helpful in determining the allocation of individuals into segments and the sizes of those segments, which describe specific attribute processing strategies.

We, therefore, contribute to the literature in several ways. First, we provide further empirical evidence of ANA in two different marketing contexts and outline the implications of the strict assumption of full attribute attendance. Second, we contribute by proposing a novel framework of how visual attention might affect choices through its implicit link to the relevance of and subsequent attendance to attributes. This further allows investigating attribute-specific differences in how attention translates into attendance. Third, we provide further validation of methods for inferring ANA based on the observed choices. We find that relying only on the observed choices can be sufficient for recovering general patterns in applied attribute processing strategies and the distribution of WTP.

The rest of the manuscript is structured as follows. In section 4.2, we review the related literature on existing approaches to incorporating ANA as well as on the use of eye tracking in studying decision-making and choice. Subsequently, we describe the methodology, including our main models as well as benchmark models, the derivation of the visual attention measure, the estimation procedure as well as measures of interest derived from the obtained parameter estimates. In section 4.4, we present and discuss the results of two empirical applications. The paper concludes with a summary and an outline of avenues for future research.

4.2 Related Literature

Our study links eye tracking with discrete choice models that account for ANA. Therefore, in the following section, we concisely review the literature on methods that explicitly account for ANA, outline general trends and recent developments in this area, and provide an overview of eye tracking research in relation to decision-making and choice.

4.2.1 Methods to Account for Attribute Non-attendance

To date, in the existing literature, two main approaches accommodating ANA can be outlined (Hensher 2014). One approach, which we will refer to as exogenous, solely relies on supplementary data collected during an experiment such as stated

ANA (e.g., Hensher 2006), attribute importance ranking (e.g., Hess and Hensher 2013) from debriefing questions, click data from Mouselab experiments (Currim et al. 2015) and measures derived from eye tracking (e.g., Balcombe et al. 2015; Meißner et al. 2011). The preference parameters in the random utility specification are then conditioned on these measures by setting them to zero (e.g., Hensher et al. 2005), rescaling them downwards ("shrinking"; e.g., Balcombe et al. 2015), or estimating a separate set of parameters for non-attenders (e.g., Hess and Hensher 2010). Each of the auxiliary measures used has certain limitations. In particular, stated ANA is a subjective measure and depends on the recall, belief, and motivation of the respondents (Hess and Hensher 2010). On the other hand, Mouselab experiments may influence the respondents' information search process (Glöckner and Betsch 2008). In contrast, in the case of the more objective eye tracking measure (Meißner and Oll 2017), one needs to derive a discrete measure for use as a proxy for ANA. For example, Balcombe et al. (2015) use fewer than two fixations as an indicator of ANA in a given choice task. If the attribute was not attended to in more than half of the choice tasks, it is considered non-attended throughout the choice experiment. However, the choice of the cutoff in each and across all choice tasks may influence the model outcomes. Moreover, attribute-specific cutoffs might be more suitable, as some attributes may require more "looking," depending on how they are presented (e.g., as a picture or text)[4]. In the case ofFor all those measures, a common limitation of the exogenous methods remains their deterministic use (i.e., assuming a one-to-one relationship with ANA).

To address this limitation, several scholars have proposed inferring ANA from the observed choices rather than solely relying on additional data (Hensher 2014). We refer to this class of approaches as endogenous methods. Within this framework, e.g., Hess and Hensher (2010) suggested inferring ANA on the basis of high dispersion of the individual-level conditional parameter distribution. By contrast, Scarpa et al. (2009) and Hole (2011) propose a latent class approach probabilistically allocating individuals into a priori defined classes that are based on (many or) all possible attendance/non-attendance combinations, i.e., attribute processing strategies. This approach was shown to outperform the exogenous approach relying on the stated ANA measure (Scarpa et al. 2013). Endogenous models were further developed to simultaneously accommodate heterogeneity in individual preferences (Gilbride et al. 2006; Hess et al. 2013; Hole et al. 2013). As Hess et al. (2013) and Hole et al. (2013) demonstrate, neglecting preference heterogeneity may result in an overstatement of the amount of ANA, as the model may not correctly distinguish between zero and low sensitivity.

[4]One way of identifying optimal cutoffs could be by, e.g., employing a grid-search. However, the optimization problem can become rather complex in the case of attribute-specific cutoff values.

A few scholars have proposed further augmenting these models by conditioning class allocation on auxiliary information. For example, Swait et al. (2016) have used complexity measures, potentially capturing task-driven ANA. However, Alemu et al. (2013), using debriefing questions, establish that true irrelevance of the attributes is a common reason for ANA. By contrast, Hole et al. (2013) and Collins et al. (2013) use stated ANA as a covariate, which should capture different drivers of ANA. Nevertheless, the objectivity and reliability of this measure remain an issue.

We build upon the outlined developments in the ANA literature and adopt an endogenous approach for incorporating ANA. We simultaneously account for heterogeneity in preferences (Hole et al. 2013) and, in contrast to the existing literature, condition the class allocation on a measure of visual attention derived from eye tracking. Notably, the main body of research on ANA streams from other fields, including transportation, environmental and health economics. However, ANA has practical relevance and importance in marketing, given the large variation in characteristics for the choice situations consumers face.

4.2.2 Eye Tracking, Decision-making and Choice

Eye tracking has a long history in psychology and marketing research and has been used in diverse settings to understand attentional processes, search behavior and choice (Wedel and Pieters 2008). As eye movements are considered to be representative of covert attention and cognitive processes (Wedel and Pieters 2008), it has been paramount in studying consumer decision-making (see Orquin and Loose 2013 for a comprehensive review).

For example, Shi et al. (2013) study the information acquisition of consumers on comparison websites. Notably, they find that not all alternatives and attributes receive attention or are discarded at the decision stage. Meißner et al. (2016) explore attentional processes in CBC. They show that repeated choices reinforce the ease of finding relevant information and that through the sequence of choice tasks, respondents become more selective and faster at acquiring information. Orquin et al. (2018) further demonstrate that predictability of the location of the information, which is the case in CBC, increases (decreases) the likelihood of looking at information of high (low) relevance. That is, while eye movements are generally a result of both bottom-up (e.g., size of the stimuli) and top-down (e.g., consumer goals) factors, due to the learning that occurs in repeated choices, the latter prevails (Orquin et al. 2013).

Other studies use eye tracking to relate attention to preferences (e.g., Toubia et al. 2012), consideration set formation (e.g., Chandon et al. 2009), as well as choice (e.g., Pieters and Warlop 1999). Furthermore, eye tracking has been essential in studying and modeling consumer search behavior (e.g., Van der Lans et al. 2008;

Reutskaja et al. 2011; Liechty et al. 2003). Notably, several studies have proposed joint models of information search and choice. For example, Stüttgen et al. (2012) jointly model search with a satisficing choice rule, i.e., where consumers stop the evaluation process as soon as they find a satisfactory product. Yang et al. (2015) propose a dynamic search model, in which information acquisition represents a cognitive cost that must be compensated.

In contrast, we do not model information search. Instead, we are interested in the link between visual attention and the underlying attribute processing strategy. From this perspective, the studies of Balcombe et al. (2015), Meißner et al. (2011), Krucien et al. (2017), and Van Loo et al. (2018) use eye tracking in the ANA context. However, they adopt an exogenous approach of accounting for ANA, which suffers from the limitations outlined in section 4.2.1. Conversely, we use an endogenous approach that allows us to link eye fixations as a measure of visual attention that is indicative of the relevance of the attribute information (Meißner and Oll 2017) to the underlying ANA strategies in a probabilistic manner. Hence, we avoid any explicit assumptions about a causal effect of eye movements on preferences as outlined by Orquin and Loose (2013).

4.3 Methodology

We start this section by describing our main model – the mixed endogenous attribute attendance (MEAA) model – which explicitly allows us to accommodate both ANA and preference heterogeneity as well as to connect visual attention from eye tracking to the consumers' applied attribute processing strategy. We will also discuss how we derive the measure of visual attention and explain the calculation of the measures (e.g., the relative importance of attributes, WTP) and quantities (e.g., posterior probabilities) that are obtained as a transformation of the parameter estimates and used to generate insights in the empirical application.

4.3.1 Mixed Endogenous Attribute Attendance Model

The MEAA model (Hole et al. 2013) is a confirmatory latent class approach (Hess et al. 2013) that relaxes the assumption of full information processing. In particular, individuals can ignore any number and combination of attributes. Given K attributes, there exist 2^K possible attendance/non-attendance combinations or attribute processing strategies (e.g., Hess et al. 2013). In the MEAA model, for each of the possible attribute processing strategies, we have a corresponding latent class s ($s = 1, \dots, S$) that can be described by a K-dimensional column vector $\lambda_s = [\lambda_{s1}, \dots, \lambda_{sK}]'$ of zeros and ones, indicating the attributes that are ($\lambda_{sk} = 1$) and are not included ($\lambda_{sk} = 0$) in the specific class s.

In this model, the utility individual i ($i = 1,\ldots,I$) obtains from alternative j ($j = 1,\ldots,J$) in choice task t ($t = 1,\ldots,T$) is class-specific:

$$U_{ijt|s} = x_{ijt} \cdot \beta_{is} + \epsilon_{ijt}, \tag{4.1}$$

where x_{ijt} is a K-dimensional row vector of attribute values describing alternative j in choice task t for individual i, β_{is} is a column vector of corresponding preference parameters, and ϵ_{ijt} is an identically distributed type I extreme value error term. The subscripts i and s indicate that the vector of preference parameters is individual- and class-specific. The former allows incorporating preference heterogeneity, assuming the individual parameters β_i are distributed multivariate normal: $\beta_i \sim N(\beta,\Sigma)$. The class-specific parameters are obtained via the elementwise multiplication of λ_s with the individual-specific vector of parameters: $\beta_{is} = \lambda_s \circ \beta_i$. For the attributes not included in class s, the corresponding elements in λ_s set the preference parameters to zero. We use effects coding for all categorical attributes (e.g., brand) and linear specification for price-related attributes.[5] If multiple elements in x_{ijt} are related to an attribute ("attribute-levels"), we map the λ_s vector onto the correct parameter dimension, such that if attribute k is not attended all m_k attribute-levels are not attended.

To illustrate the different utility functions in each of the classes, we provide a simple example, in which products are described by three attributes, resulting in $S = 2^3 = 8$ possible classes. As the parameter estimates are switched on and off, each class is characterized by a different linear (additive) utility function, presented in Table 4.1. As a result, several decision rules are incorporated: (class 1) full compensatory (i.e., full attendance), (class 8) random choice, (classes 5-7) (a probabilistic version of) lexicographic, and (classes 2-4) semicompensatory, i.e., the compensatory rule applies only within the subset of attended attributes.

Even though we allow for ANA, we assume that individuals are utility maximizers. In doing so, we follow the bounded rationality literature, which states that individuals can still act rationally by maximizing their utility but do so based on partial and imperfect information (Rasouli and Timmermans 2015). Given the distribution of the error term, within each class s, the probability of individual i choosing alternative j in choice task t is

$$P_{ijt|s} = \frac{\exp(x_{ijt} \cdot \beta_{is})}{\sum_{j' \in J} \exp(x_{ij't} \cdot \beta_{is})}. \tag{4.2}$$

Following Hole (2011), we assume that likelihood of attending a particular attribute is independent of attending other attributes (IAA). Thus, the class

[5] Note that dummy coding is not an option here because then the reference level of an attribute has a utility of zero and cannot be differentiated from ANA (Gilbride et al. 2006).

	Utility function									Decision rule
Class 1:	$U_{ijt\|1}$	$=$	$\beta_i^1 \cdot x_{ijt}^1$	$+$	$\beta_i^2 \cdot x_{ijt}^2$	$+$	$\beta_i^3 \cdot x_{ijt}^3$	$+$	ϵ_{ijt}	Full compensatory
Class 2:	$U_{ijt\|2}$	$=$			$\beta_i^2 \cdot x_{ijt}^2$	$+$	$\beta_i^3 \cdot x_{ijt}^3$	$+$	ϵ_{ijt}	Semicompensatory
Class 3:	$U_{ijt\|3}$	$=$	$\beta_i^1 \cdot x_{ijt}^1$	$+$			$\beta_i^3 \cdot x_{ijt}^3$	$+$	ϵ_{ijt}	Semicompensatory
Class 4:	$U_{ijt\|4}$	$=$	$\beta_i^1 \cdot x_{ijt}^1$	$+$	$\beta_i^2 \cdot x_{ijt}^2$	$+$			ϵ_{ijt}	Semicompensatory
Class 5:	$U_{ijt\|5}$	$=$	$\beta_i^1 \cdot x_{ijt}^1$	$+$					ϵ_{ijt}	Lexicographic
Class 6:	$U_{ijt\|6}$	$=$			$\beta_i^2 \cdot x_{ijt}^2$	$+$			ϵ_{ijt}	Lexicographic
Class 7:	$U_{ijt\|7}$	$=$					$\beta_i^3 \cdot x_{ijt}^3$	$+$	ϵ_{ijt}	Lexicographic
Class 8:	$U_{ijt\|8}$	$=$							ϵ_{ijt}	Random choice

Notes: The upper notation indicates the preference parameter for a particular attribute (variable): β_i^k

Table 4.1. Class characteristics in case of 3 attributes

probabilities τ_{is} (where $0 \leq \tau_{is} \leq 1$ and $\sum_{s=1}^{S} \tau_{is} = 1$) are modeled as a mapping from the attribute attendance probabilities, π_{ik}, which are parametrized as a logistic function:

$$\tau_{is} = \prod_{k=1}^{K} \pi_{ik}^{\lambda_{sk}} \cdot (1-\pi_{ik})^{1-\lambda_{sk}}, \quad \text{with} \quad \pi_{ik} = \frac{\exp(z_{ik} \cdot \gamma)}{1+\exp(z_{ik} \cdot \gamma)}, \tag{4.3}$$

where z_{ik} is a row vector with K attribute-specific intercepts and (possibly) E attribute-specific individual-level variables (e.g., revealed or stated ANA) with corresponding parameter vector γ. Note that the additional variables entering z_{ik} are optional, and the MEAA model can be estimated without any extra information. In this case, the attribute attendance probabilities π_{ik} and respective class probabilities τ_{is} are common across individuals, and the subscript i can be dropped. The submodel in Equation (4.3) is closely related to the model proposed by Swait and Ben-Akiva (1987) for modeling choice set heterogeneity and to the concomitant latent class models of Kamakura et al. (1994). Although the IAA assumption seems restrictive, it ensures parsimony and the practicality of the model because the number of parameters rises linearly with K, not S, as would be the case if we use a multinomial logit model for τ_{is} with $S-1$ class-specific intercepts (Hole 2011). In addition to the loss of parsimony, relaxing the IAA assumption may reduce model stability (i.e., issues with local maxima) while offering only marginal improvements in fit (Hess et al. 2013).

The unconditional probability of individual i choosing alternative j in choice task t can be derived by combining Equations (4.2) and (4.3), where τ_{is} can be interpreted as the size of class s and is the prior probability of finding individual i in class s:

$$P_{ijt} = \sum_{s=1}^{S} \tau_{is} \cdot P_{ijt|s}. \tag{4.4}$$

The utility function in Equation (4.1) allows a straightforward derivation of restricted models, which do not include either ANA, preference heterogeneity or both. For example, by setting $\tau_1 = 1$ (i.e., everyone belongs to class 1 with full attendance), the MEAA model is reduced to the mixed multinomial logit (MMNL) model. By setting $\Sigma = \mathbf{0}$ while retaining all S classes, the MEAA reduces to the endogeneous attribute attendance (EAA) model proposed by Hole (2011). Combining both restrictions leads to the multinomial logit (MNL) model. Hence, the MNL, EAA, and MMNL models are all special cases of the MEAA model and will serve as benchmarks in the empirical application.

4.3.2 Estimation Procedure

For statistical inference, we employ maximum likelihood estimation with sample log-likelihood $LL(\theta) = \sum_{i \in I} \ln(L_i)$ where L_i is the likelihood of individual i, and θ denotes the vector of unknown parameters $\theta = [\beta, \text{vec}(\Sigma), \gamma]'$. For the MEAA model, L_i is the weighted sum of the respective class-specific likelihoods, i.e., $L_i = \sum_{s=1}^{S} \tau_{is} \cdot L_{i|s}$. The latter represents the sequence of observed choices for individual i conditional on class s because the data have a panel structure (i.e., t choice tasks for each individual i), and we assume that individuals do not change the attribute processing strategy across tasks:

$$L_{i|s} = \int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|s}^{y_{ijt}} \phi(\beta_i | \beta, \Sigma) d\beta_i, \tag{4.5}$$

where y_{ijt} is a dummy indicating whether alternative j was chosen by individual i in choice task t, and ϕ is the density of the normal distribution. For the MMNL model, no weighting by class probabilities is necessary. For the EAA model, preference parameters are homogeneous, and therefore no integration over the parameter distribution is required. For the MNL model, neither integration over the parameter distribution nor weighting by class probabilities is required.

As the integral over the density of β_i in Equation (4.5) has no closed-form solution, we adopt the simulated maximum likelihood approach and approximate it using 500 Halton draws (Train 2009). We estimate all parameters simultaneously using the gradient-based Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (see Train 2009, p. 225). Because latent class models may have multiple local optima (see Wedel and Kamakura 2000), multiple starting values were tested to find the global optimum (Dayton and Macready 1988).

4.3.3 Postestimation Measures

Based on the estimated parameters, we derive several quantities that are essential for our analysis. In the (M)EAA models, we can segment respondents into the specific classes of attribute processing strategies, and for this, we use the estimated parameters $\hat{\theta}$ in Equations (4.3) and (4.5) to obtain posterior class probabilities via Bayes' rule (Wedel and Kamakura 2000):

$$\hat{\tau}_{is}^{\text{post.}} = \frac{\hat{\tau}_{is} \cdot L_{i|s}}{\sum_{s'=1}^{S} \hat{\tau}_{is'} \cdot L_{i|s'}}, \tag{4.6}$$

Here, the prior class probabilities are reweighted by the estimated likelihood of each individual i conditional on class s. The resulting posterior class probabilities represent a "fuzzy" segmentation criterion, and individuals can be fractional members of (multiple) attribute processing strategy segments. Given our assumption that each individual has a specific attribute processing strategy, we opt for a nonoverlapping segmentation and assign individuals to the class where the value of $\hat{\tau}_{is}^{\text{post.}}$ is the highest (cf. Desarbo et al. 1995). To assess the degree of overlap, we use the entropy (Wedel and Kamakura 2000):

$$\text{entropy} = 1 + \frac{\sum_{i=1}^{I} \sum_{s=1}^{S} \hat{\tau}_{is}^{\text{post.}} \cdot \ln\left(\hat{\tau}_{is}^{\text{post.}}\right)}{I \cdot \ln(S)}. \tag{4.7}$$

This measure is bound between 0 and 1, with values of zero indicating complete overlap between class allocations (i.e., all posterior class probabilities are equal) and values close to one implying a more certain class assignment with minimal overlap.

Furthermore, we derive some key measures that represent a transformation of the estimated preference parameters such as the relative importance of attributes and WTP, which have practical significance for marketing managers (Rao 2014). We base these measures on the conditional individual-level estimates $\hat{\beta}_{is}$; i.e., we utilize all the available information (e.g., observed choices and other individual-level information) in a submodel of class probabilities in Equation (4.3) to increase the accuracy of the preference estimate for a given individual (Hensher et al. 2015).

After obtaining the class for each individual with the highest value of $\hat{\tau}_{is}^{\text{post.}}$, denoted by $\hat{s}$, for models with preference heterogeneity (i.e., MMNL, MEAA, and MEAA(va)) we employ Bayes' rule again to condition on the observed choices and compute the posterior means of the parameters on the individual level (Train 2009):

$$\hat{\beta}_{i\hat{s}}^{\text{post.}} = \frac{\int \hat{\beta}_{i\hat{s}} \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|\hat{s}}^{y_{ijt}} \phi(\beta_i|\beta, \Sigma) d\beta_i}{\int \prod_{t=1}^{T} \prod_{j=1}^{J} P_{ijt|\hat{s}}^{y_{ijt}} \phi(\beta_i|\beta, \Sigma) d\beta_i}, \tag{4.8}$$

where we again employ a simulation method with Halton draws to approximate the integrals. We use this definition of individual estimates because it preserves the value zero on the individual level if i is classified as a non-attender. This feature is essential in marketing applications because it also translates into the derived measures, such as relative importance and WTP (as described next). For the MMNL model, we do not have to condition on a specific class.

The relative importance of an attribute is the ratio of its utility range to the sum of the utility ranges of all attributes (Rao 2014). We compute the utility ranges on the individual level from $\hat{\beta}_{i\hat{s}}^{\text{post.}}$. Furthermore, we use two aggregate measures for the (M)EAA model (similar to Gilbride et al. 2006). First, we calculate the mean across all individuals, including individuals who did not attend to attribute k and have a corresponding relative importance of zero. Second, we are interested in assessing this measure for individuals who, in fact, attended to the specific attribute; hence, we compute the average for this subset of individuals. For targeting specific segments, this measure of relative importance entails essential and relevant information for managers.

We compute individual WTP values from $\hat{\beta}_{i\hat{s}}^{\text{post.}}$ by dividing the parameters (respectively, the differences in attribute-level related parameters) of nonprice related attributes by the negative price parameter. Hence, conveniently, we rescale the utility of each attribute in monetary units (Rao 2014). Following a similar logic as that used for the relative importance computation, we derive an average WTP for an attribute across all and one across the subset of individuals who attended to the attribute.

4.3.4 Measure of Visual Attention

Subsequently, we use a continuous measure of visual attention derived from eye tracking as additional individual-level information, which enters z_{ik} in Equation (4.3) in the (M)EAA model specification. This is similar to the inclusion of consumer descriptors (concomitant variables) in latent class models (Kamakura et al. 1994; Wedel and Kamakura 2000). For example, Gupta and Chintagunta (1994) use demographics in the context of brand choice using scanner panel data and Swait and Adamowicz (2001) employ complexity measures when modeling choices in a stated choice experiment. Generally, the additional information used as a covariate in the submodel of class probabilities proves to increase model fit and aids with the identification of the latent classes (Dayton and Macready 1988).

We use eye fixations as an input for our metric. This choice from among the possible eye tracking metrics is motivated by the fact that the number of fixations is one of the most commonly used proxies indicating information acquisition and attention (Wedel and Pieters 2008) and has been previously used in the context of ANA (e.g., Balcombe et al. 2015). Furthermore, in line with previous literature, we also find it to be highly correlated with fixation duration. In CBC, the information in each choice task is presented in matrix form, where attributes are typically presented as rows and alternatives as columns. Given K attributes and J alternatives, this results in a $K \times J$ matrix, with each (k, j) element characterizing attribute k for alternative j. We define each of the (k, j) elements as a separate area of interest. In a given task t for each individual i, we count the number of fixations on each area of interest, i.e., the (k, j) element. As non-attendance is defined for an attribute (and not its levels), we the sum the number of fixations for each row k across all J alternatives, and as we are interested in the overall attention pattern, we further sum across all T choice tasks. Next, we standardize this measure within each individual to control for potential heterogeneity and label it as va_{ik}. Our motivation for standardization is similar to that in Pieters and Warlop (1999), where the visual attention measure is centered for each individual to control for differences in experimental conditions.

Using va_{ik} as additional information in z_{ik} should help to model π_{ik} and, therefore, τ_{is}. In particular, we expect a positive effect of va_{ik} on π_{ik}. Nevertheless, the probabilistic relationship between visual attention and the particular attribute processing strategy, in contrast to exogenous approaches to accommodating ANA, allows for the possibility that looking at given information does not guarantee that it is deployed in decision-making.

4.4 Empirical Application

We start the following section by describing the two datasets we chose for our empirical application. We then continue with a detailed discussion of the estimation results, e.g., model fit, parameter estimates, including the effect of visual attention, as well as the differences in subsequent individual class memberships, the relative importance of attributes and WTP.

4.4.1 Data

We employ two studies involving choices in different durable product categories: coffee makers and laptops, conducted by Meißner et al. (2016) and Yang et al. (2015), respectively. Both combine a CBC study with an eye tracking experiment, i.e., eye movements of the respondents were simultaneously tracked while they completed the choice tasks (for details on the eye tracking devices used and the experimental setup, we kindly refer the reader to the respective articles). We chose these two datasets because they represent typical CBC studies used in marketing research. Therefore, the results of our analysis are relevant to a broader marketing audience. However, they differ in terms of the product category and some features of the experimental setup and design presented in Table 4.2, which enables us to validate that the general patterns we find hold across contexts.

Study	Coffee makers	Laptops
Number of respondents:	$I = 59$	$I = 70$
Number of choice tasks:	$T = 12$	$T = 20$
Number of alternatives:	$J = 3$ + none	$J = 4$
Number of attributes:	$K = 6$	$K = 6$
Attributes (number of levels):	Brand (4), material (3), system (2), design (4), price per cup (3), price (4)	Speed (4), size (4), capacity (4), support (4), antivirus (4), price (4)
Number of potential classes:	$S = 64$	$S = 64$
Choice task design:	Orthogonal and level balanced	Random design
Randomization across subjects:	Yes	No
Incentive alignment:	No	Yes
Source:	Meißner et al. (2016)	Yang et al. (2015)

Table 4.2. Description of datasets

In both cases, the respondents were sampled from students of European universities. After excluding responses with incomplete data or a straight-lining pattern, we obtain samples of 59 (coffee makers) and 70 (laptops) respondents, which is a typical sample size for eye tracking experiments. The studies vary in the number of choice tasks: 12 in coffee maker study and 20 in the laptop study. A “none” option was included in the coffee maker study, with an average choice share of 15.4%. The rest of the choice shares were equally distributed among the three alternatives. In the laptop study, the average choice share distribution was slightly less balanced, ranging from 21 to 30%. Additionally, the laptop study was incentive-aligned, but without a “none” option, which makes it inappropriate for WTP calculation (Allenby et al. 2014). The studies further differ in presentation format. In particular, the attributes in the coffee maker study vary in terms of information type: pictorial (e.g., *design* and *system*), numeric (e.g., *price*) or textual (e.g., *brand*), font size, and color (see Figure 1 in Meißner et al. 2016, p. 5). By contrast, the laptop study uses a standardized information presentation format that contains mainly numeric information and uses similar font sizes and colors across attributes (see Figure 1 in Yang et al. 2015, p. 168). Both studies include six attributes, resulting in 64 possible attribute processing strategies. Therefore, we can investigate how well the models can identify the particular strategy applied by an individual given these many possibilities.

Regarding the eye tracking information, we observe that on average, respondents fixate 41 (58) times per choice task in the coffee maker (laptop) study, with substantial variation across respondents (standard deviation (SD) of 25 (34) in the coffee maker (laptop) study). We also observe differences in the number of fixations across attributes. In particular, on average *price* and *price per cup* receive the highest number of fixations per task in the coffee maker study (approx. 8.40), followed by *system* (6.80), *material* (6.21), *design* (6.16), and *brand* (4.77). In the laptop study, *speed* receives the highest (15) number of fixations per task, followed by *size*, *capacity*, and *price* (10-12) and *support* and *antivirus* (approx. 5). The per task fixations on a given attribute range from 0 up to 32 for *design* and up to 89 for *price per cup* in the coffee maker study, up to 41 for *antivirus* and as much as up to 82 for *speed* in the laptop study. However, across choice tasks, all respondents fixate on all attributes. Considering that we define non-attendance for an attribute and not its levels and that we are interested in the overall pattern of attention across tasks, we derive our person-attribute specific measure of visual attention as described in section 4.3.4. In both datasets, the measure varies substantially across attributes (mean ranging from -0.70 to 0.53 for coffee makers and from -0.95 to 1.13 for laptops), across individuals (SD ranging from 0.75 to 0.89 for coffee makers and 0.24 to 0.79 for laptops), as well as within individuals (average range across individuals of 2.59 for coffee makers and 2.51 for laptops). This variation, therefore, allows identification of the parameter estimates, and hence we conclude that both datasets are well suited for our analysis.

4.4.2 Model Comparison

For each of the datasets, we have estimated six models, MNL, MMNL, EAA, EAA(va), MEAA, and MEAA(va), where “va” indicates that the models include the visual attention measure. In the initial solutions, the MEAA and MEAA(va) models had very large and positive intercept estimates in the submodel of the class probabilities in Equation (4.3) for the attributes *price* (coffee makers) and *support* (laptops). Note that this is not an issue and only shows that there is no ANA for these attributes after controlling for preference heterogeneity (Hole et al. 2013). Hence, we simply re-estimated the models setting these attributes to 100% attendance. Thus, for both datasets, $2^5 = 32$ possible attribute processing strategies (or classes) are available. We also included a dummy variable for the “none” option in the coffee maker study but did not allow for ANA here, as “none” is not a product attribute. Additionally, we estimated the heterogeneous models with a diagonal specification of Σ for reasons of parsimony. We report the final estimation results in Tables 4.3 and 4.4.

In general, we are interested in several comparisons. First, by contrasting models with and without heterogeneity, we aim to validate the importance of accounting for preference heterogeneity, primarily due to potential confounding with ANA. Second, by comparing the models that assume full attendance with those including ANA, we outline the implications of neglecting the latter in a marketing context. Third, we compare models that include the measure of visual attention (i.e., EAA(va) and MEAA(va)) vs. “regular” ANA models (i.e., EAA and MEAA).

For the comparison of in-sample fit across models, we use log-likelihood (LL) and McFadden’s R^2 (ρ^2) (see Wedel and Kamakura 2000). ρ^2 offers an intuitive

		MNL	**EAA**	**EAA(va)**	**MMNL**	**MEAA**	**MEAA(va)**
Utility Parameters							
None	β	-0.19 (0.11)	0.33 (0.13)	0.30 (0.14)	-2.46 (0.87)	-2.53 (0.96)	-2.64 (0.91)
	σ				4.39 (0.78)	4.48 (0.85)	4.67 (0.81)
Brand: Braun	β	0.06 (0.09)	1.51 (0.49)	0.60 (0.50)	0.08 (0.14)	0.52 (0.47)	0.43 (0.32)
	σ				0.39 (0.16)	0.55 (0.37)	0.63 (0.33)
Brand: Krups	β	0.01 (0.09)	0.69 (0.49)	0.38 (0.38)	-0.02 (0.12)	0.15 (0.39)	0.33 (0.41)
	σ				0.05 (0.26)	0.88 (0.45)	0.62 (0.33)
Brand: Philips	β	0.23 (0.09)	0.99 (0.54)	0.62 (0.33)	0.38 (0.12)	0.90 (0.34)	0.68 (0.28)
	σ				0.26 (0.18)	0.16 (0.48)	0.71 (0.35)
Material:	β	0.51 (0.07)	1.52 (0.19)	1.43 (0.19)	0.78 (0.11)	1.87 (0.30)	1.70 (0.22)
Stainless steel	σ				0.40 (0.13)	0.36 (0.26)	0.30 (0.19)
Material:	β	-0.51 (0.08)	-1.67 (0.25)	-1.51 (0.24)	-0.80 (0.12)	-2.01 (0.35)	-1.78 (0.27)
Plastic	σ				0.41 (0.16)	0.60 (0.40)	0.53 (0.27)
System: Pad	β	0.22 (0.05)	1.73 (0.24)	1.50 (0.20)	0.33 (0.12)	1.99 (0.28)	1.90 (0.28)
	σ				0.79 (0.14)	0.16 (1.07)	0.51 (0.40)
Design: A	β	-0.29 (0.09)	-2.20 (0.75)	-1.81 (0.53)	-0.48 (0.13)	-2.61 (1.09)	-2.06 (0.58)
	σ				0.01 (0.21)	0.02 (0.84)	0.05 (0.48)
Design: B	β	0.03 (0.09)	0.32 (0.37)	0.25 (0.34)	0.05 (0.12)	0.31 (0.43)	0.23 (0.36)
	σ				0.09 (0.17)	0.17 (0.53)	0.19 (0.44)
Design: C	β	0.13 (0.09)	1.40 (0.41)	1.26 (0.30)	0.24 (0.12)	1.73 (0.72)	1.43 (0.35)
	σ				0.20 (0.28)	0.47 (0.52)	0.07 (0.40)
Price per cup	β	-0.80 (0.07)	-1.76 (0.18)	-1.74 (0.16)	-1.34 (0.16)	-1.77 (0.28)	-1.90 (0.22)
	σ				0.83 (0.14)	0.86 (0.20)	0.64 (0.19)
Price	β	-2.12 (0.17)	-3.72 (0.36)	-3.72 (0.33)	-3.45 (0.39)	-4.19 (0.48)	-4.13 (0.43)
	σ				1.78 (0.34)	1.61 (0.43)	1.59 (0.40)
Class Parameters							
Brand			-2.08 (0.69)	-0.08 (1.46)		-0.54 (0.82)	1.59 (1.48)
Material			-0.15 (0.35)	0.28 (0.52)		-0.03 (0.36)	0.86 (0.60)
System			-1.42 (0.38)	-1.84 (0.47)		-1.01 (0.33)	-2.02 (0.64)
Design			-1.76 (0.58)	-2.05 (0.66)		-1.72 (0.60)	-2.64 (0.87)
Price per cup			0.57 (0.37)	-0.13 (0.48)		2.08 (1.29)	0.72 (0.71)
Price			1.60 (0.53)	1.03 (0.58)			
Visual attention				1.94 (0.36)			2.88 (0.66)
Number of parameters		12	18	19	24	29	30
In-sample							
LL		-745.11	-688.89	-656.50	-600.81	-578.33	-540.66
BIC		1568.98	1495.90	1437.68	1359.11	1346.96	1278.19
ρ^2		0.24	0.30	0.33	0.39	0.41	0.45
Out-of-sample							
Hitrate		0.55	0.57	0.60	0.64	0.67	0.68
Hitprob		0.43	0.49	0.51	0.59	0.62	0.63

Note: standard errors are indicated in parentheses.

Table 4.3. Estimation results for the coffee maker study

interpretation, with values between 0.2 and 0.4 indicating a very good fit (Louviere et al. 2000). We also use the Bayesian information criterion (BIC) for model selection. Compared to LL, BIC penalizes for model complexity and can be used for the comparison of non-nested models.[6]

First, the models fit the data in both applications quite well. Furthermore, as suggested by the smaller BIC, larger ρ^2, and LL-values, all heterogeneous models outperform their homogeneous counterparts in both applications. For example, the MEAA model outperforms the EAA model and the MEAA(va) model outperforms the EAA(va) model. Moreover, the MMNL model outperforms all homogenous models, including the best-fitting EAA(va) model. Thus, relaxing

[6] Note that the MEAA model nests all other models at the boundary of the parameter space, hence the LL ratio test is not applicable (McLachlan and Peel 2000).

		MNL	EAA	EAA(va)	MMNL	MEAA	MEAA(va)
Utility Parameters							
Speed: 1.6 Ghz	β	-1.69 (0.11)	-2.26 (0.19)	-2.72 (0.20)	-2.71 (0.21)	-3.16 (0.26)	-3.00 (0.24)
	σ				1.15 (0.15)	0.89 (0.15)	1.08 (0.16)
Speed: 1.9 Ghz	β	-0.69 (0.09)	-0.91 (0.12)	-1.14 (0.13)	-1.17 (0.13)	-1.46 (0.16)	-1.36 (0.16)
	σ				0.24 (0.16)	0.56 (0.15)	0.07 (0.34)
Speed: 2.7 Ghz	β	0.98 (0.09)	1.19 (0.12)	1.45 (0.13)	1.62 (0.13)	1.84 (0.16)	1.73 (0.15)
	σ				0.39 (0.12)	0.01 (0.23)	0.24 (0.18)
Size: 26 cm	β	-0.31 (0.06)	-1.68 (0.24)	-2.04 (0.24)	-0.44 (0.14)	-0.38 (0.22)	-0.07 (0.28)
	σ				1.34 (0.16)	2.25 (0.33)	2.69 (0.40)
Size: 35.6 cm	β	0.22 (0.08)	0.11 (0.17)	0.23 (0.18)	0.29 (0.13)	0.76 (0.23)	0.74 (0.22)
	σ				0.73 (0.12)	0.84 (0.14)	0.97 (0.16)
Size: 40 cm	β	-0.03 (0.09)	0.41 (0.19)	0.52 (0.22)	0.00 (0.12)	0.13 (0.20)	0.06 (0.20)
	σ				0.13 (0.16)	0.21 (0.25)	0.51 (0.27)
Capacity: 160 GB	β	-1.16 (0.10)	-1.99 (0.19)	-2.11 (0.19)	-1.82 (0.16)	-2.48 (0.26)	-2.40 (0.24)
	σ				0.69 (0.11)	0.56 (0.17)	0.43 (0.17)
Capacity: 320 GB	β	0.05 (0.08)	0.23 (0.12)	0.15 (0.12)	0.05 (0.12)	0.08 (0.14)	0.05 (0.14)
	σ				0.06 (0.13)	0.07 (0.24)	0.33 (0.13)
Capacity: 500 GB	β	0.61 (0.08)	1.00 (0.13)	1.12 (0.11)	0.99 (0.11)	1.25 (0.14)	1.22 (0.14)
	σ				0.07 (0.10)	0.00 (0.12)	0.01 (0.10)
Support: 1 year	β	-0.15 (0.10)	0.49 (0.26)	0.78 (0.37)	-0.29 (0.13)	-0.27 (0.13)	-0.24 (0.12)
	σ				0.17 (0.13)	0.27 (0.13)	0.30 (0.13)
Support: 2 year	β	0.17 (0.08)	0.54 (0.27)	0.37 (0.42)	0.23 (0.11)	0.15 (0.11)	0.14 (0.11)
	σ				0.29 (0.11)	0.16 (0.16)	0.02 (0.19)
Support: 3 year	β	0.03 (0.07)	-0.18 (0.22)	-0.24 (0.36)	0.06 (0.10)	0.05 (0.10)	-0.02 (0.10)
	σ				0.03 (0.09)	0.01 (0.12)	0.00 (0.12)
Antivirus: 30 days	β	-0.01 (0.06)	-3.28 (0.55)	-3.29 (0.54)	-0.05 (0.09)	-3.56 (0.81)	-3.60 (0.67)
	σ				0.36 (0.11)	0.99 (0.97)	0.51 (0.73)
Antivirus: 1 year	β	-0.10 (0.09)	0.25 (0.33)	0.24 (0.33)	-0.18 (0.12)	0.05 (0.45)	0.00 (0.39)
	σ				0.12 (0.10)	0.19 (0.48)	0.30 (0.51)
Antivirus: 2 year	β	0.19 (0.09)	1.95 (0.41)	1.81 (0.38)	0.29 (0.13)	2.07 (0.51)	1.99 (0.47)
	σ				0.21 (0.13)	0.22 (0.59)	0.30 (0.38)
Price	β	-0.36 (0.03)	-0.98 (0.06)	-0.95 (0.07)	-0.56 (0.07)	-0.76 (0.11)	-1.08 (0.12)
	σ				0.95 (0.10)	0.74 (0.07)	0.66 (0.08)
Class Parameters							
Speed			2.21 (0.77)	-1.28 (0.50)		2.65 (0.79)	-0.83 (1.01)
Size			-0.89 (0.40)	-2.78 (0.49)		0.36 (0.45)	-2.74 (0.74)
Capacity			0.82 (0.41)	0.44 (0.37)		1.28 (0.49)	1.16 (0.56)
Support			-1.37 (0.77)	0.08 (1.28)			
Antivirus			-2.57 (0.49)	-0.70 (0.56)		-2.47 (0.53)	0.72 (0.79)
Price			-0.18 (0.26)	-0.52 (0.36)		2.31 (2.20)	1.39 (0.60)
Visual attention				2.34 (0.35)			4.79 (0.84)
Number of parameters		16	22	23	32	37	38
In-sample							
LL		-1415.82	-1199.59	-1164.76	-1111.62	-1067.89	-1020.64
BIC		2947.56	2558.56	2496.14	2455.05	2403.81	2316.56
ρ^2		0.27	0.38	0.40	0.43	0.45	0.47
Out-of-sample							
Hitrate		0.56	0.61	0.63	0.70	0.70	0.70
Hitprob		0.43	0.54	0.55	0.62	0.64	0.64

Note: standard errors are indicated in parentheses.

Table 4.4. Estimation results for the laptop study

the assumption of homogeneity in preferences is crucial, including for models that accommodate ANA. In addition, in both applications, there is more to gain by accounting only for preference heterogeneity vs. only for ANA. Second, the MEAA and MEAA(va) models outperform the MMNL model, while the EAA and EAA(va) models outperform the MNL model, i.e., in general, accounting for ANA leads to considerable improvement in model fit across both applications. Finally, the MEAA(va) model is, overall, the best-fitting model and outperforms the MEAA model in both studies, even after accounting for model complexity. Similarly, the

EAA(va) model outperforms the EAA model. Hence, the visual attention measure is a useful indicator of ANA.[7]

To assess the predictive validity of the models, we additionally report hit rate and hit probability as common measures of out-of-sample fit (Gilbride et al. 2006). Using the individual-level posterior parameter estimates, we computed the measures from leave-one-out cross-validation (Maldonado et al. 2015). In each fold, we randomly left out one choice task for each respondent, repeated this procedure T times, and averaged the results. Hence, all observations are also used once in the validation, which increases the robustness of the results, however, at the cost of the need for T estimation runs. The hit rate is the average rate of correct predictions across the individuals. However, it does not convey any information on the "certainty" of the prediction. By contrast, hit probability, as the average predicted probability of the chosen alternative across the sample, does. These measures confirm the in-sample model selection results. Although the relative differences across models are somewhat smaller, we do not detect overfitting. In general, all the heterogeneous models fit very well both in-sample (ρ^2 values of over 0.39) and out-of-sample (hit rate of more than 0.64 and hit probability of more than 0.59 among four alternatives). Therefore, getting any additional improvement out-of-sample is challenging. We would, hence, consider the MEAA(va) model to be more reliable. As we will show, they generate somewhat different insights, particularly on the individual level.

4.4.3 Parameter Estimates

The resulting parameter estimates are presented in the upper panels in Tables 4.3 and 4.4. In general, the estimates across all models in both studies have face validity (e.g., negative price parameters) and reasonable magnitudes. However, we do observe relevant differences in utility parameters across models. We observe both increases and decreases in the magnitudes when moving from the worse-fitting (M)MNL models to the better-fitting (M)EAA and (M)EAA(va) models. For example, in the MEAA and MEAA(va) models, the mean price parameter increases in magnitude compared to the MMNL model, while the heterogeneity (i.e., σ) decreases. As we find some level of non-attendance to *price* in the laptop

[7] As an additional validation exercise, we have used the derived measure of visual attention in an exogenous approach. Using a grid search, we determined the cutoff value for building the discrete indicator of ANA. The corresponding attributes are then set to zero in the MNL and MMNL models. These benchmark models (which can be estimated using standard software) outperform the MNL and MMNL models and generate a similar fit compared to the EAA and MEAA models. Additionally, we have tested an alternative specification of the visual attention measure, assuming higher informativeness (and therefore weights) of the measure for the later choice tasks due to potential learning effects. In particular, we have assumed a logarithmic function for deriving the weights for the choice task number. Testing this measure using the simple EAA(va) model did not clearly improve model fit for both data sets and led to substantively similar results. The results are available from the authors upon request.

study, it is expected that some of the heterogeneity recovered in the MMNL model is now captured by the non-attendance class, shifting the mean away from zero and implying less continuous heterogeneity. For the coffee maker study, the shift in the price estimate initially seems counterintuitive considering it is fully attended. However, as Hess et al. (2013) state, such changes may also depend on the specification of other attributes. Along with the potential scale differences, the latter complicates the direct comparison of the utility estimates. Assuming that the true model includes preference heterogeneity and ANA, the results show that neglecting the latter leads to biased estimates.

Turning to the class parameters in the (M)EAA models, we see large differences in the intercepts across attributes in both datasets. This already indicates differences in the attribute attendance probabilities, and interestingly, the differences in intercepts persist in models including the visual attention measure. Regarding the latter, we observe a positive and significant effect in both applications, i.e., a higher level of visual attention generally results in a higher likelihood of attending an attribute. Notably, the magnitude of the effect increases in the MEAA(va) compared to the EAA(va) model potentially due to the confounding of preference heterogeneity and ANA. As visual attention should be indicative of non-attendance rather than low sensitivity, by better isolating these two in the MEAA(va) model, the relationship between visual attention and attribute attendance becomes more pronounced. We find further support of the confounding effect when examining the average attribute attendance probabilities presented in Figure 4.1. In particular, in both studies for almost all attributes, attendance probabilities are higher in the MEAA models, becoming 100% for *price* in coffee makers and *support* in laptops.

The higher attribute attendance probabilities also translate into a higher probability of attending more attributes, as evident from the shift of the probability distribution of the number of attended attributes to the right for the MEAA models (see Figure 4.2). Analyzing the choices regarding prescription drugs and commuting routes, respectively, Hole et al. (2013) and Hess et al. (2013) also find that many attributes become 100% attended after accounting for heterogeneity. However, we still see a considerable amount of non-attendance for most of the attributes in our two applications. For example, except *price* and *price per cup*, the attendance probabilities for all other attributes in the coffee maker study remain below 50%, resulting in the majority of respondents attending to three out of six attributes in the MEAA models. One potential explanation is the differences in the level of involvement and the associated risk of the decision in the various contexts. We find further supporting evidence by noting that the levels of non-attendance are lower in the laptop study, potentially due to incentive alignment and a higher risk related to financial cost. Additionally, we observe a larger shift of the probability distribution for the number of attended attributes to the right in the MEAA models, with the

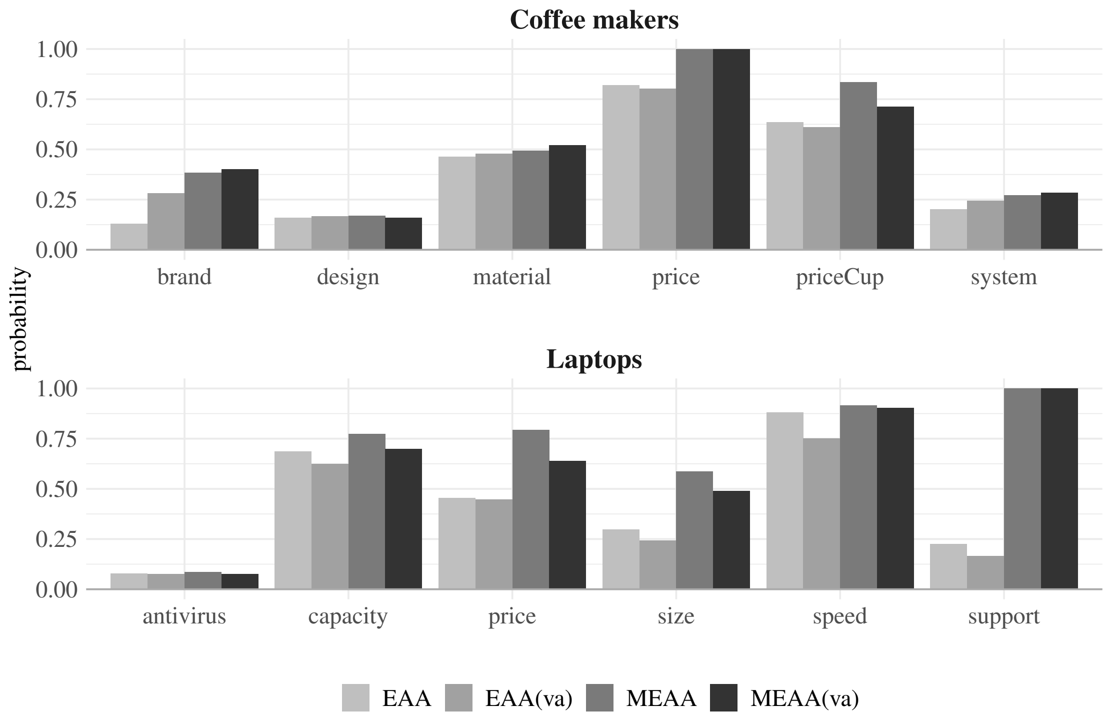


Figure 4.1. Attribute attendance probabilities

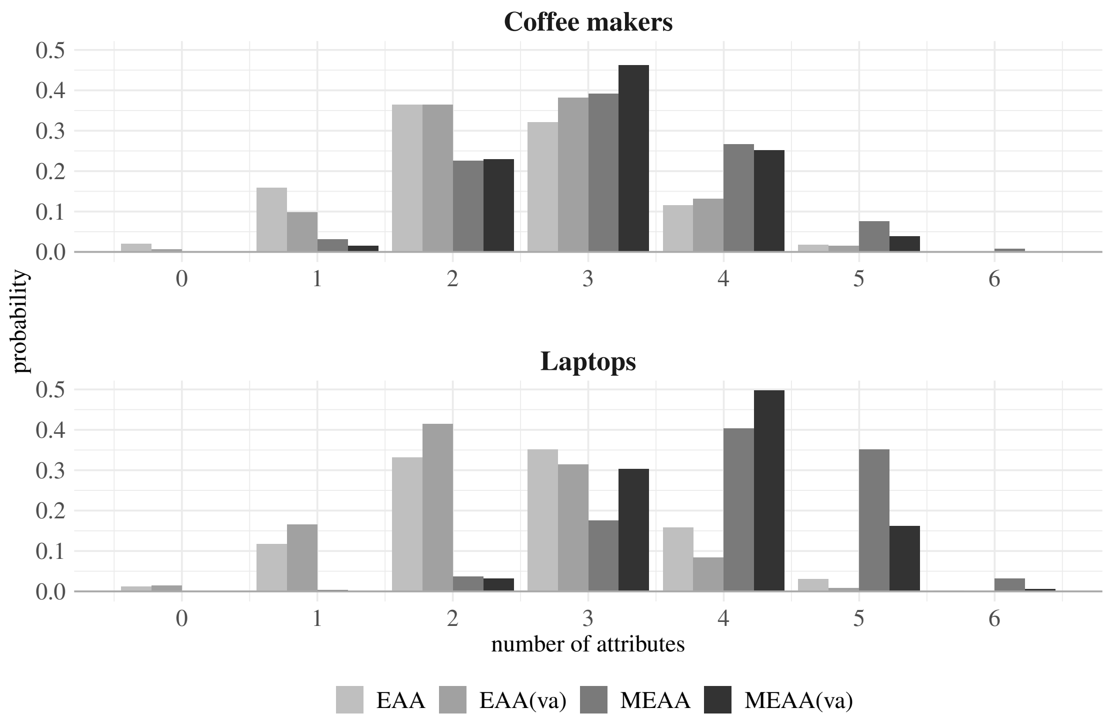


Figure 4.2. Probability of attending a certain number of attributes

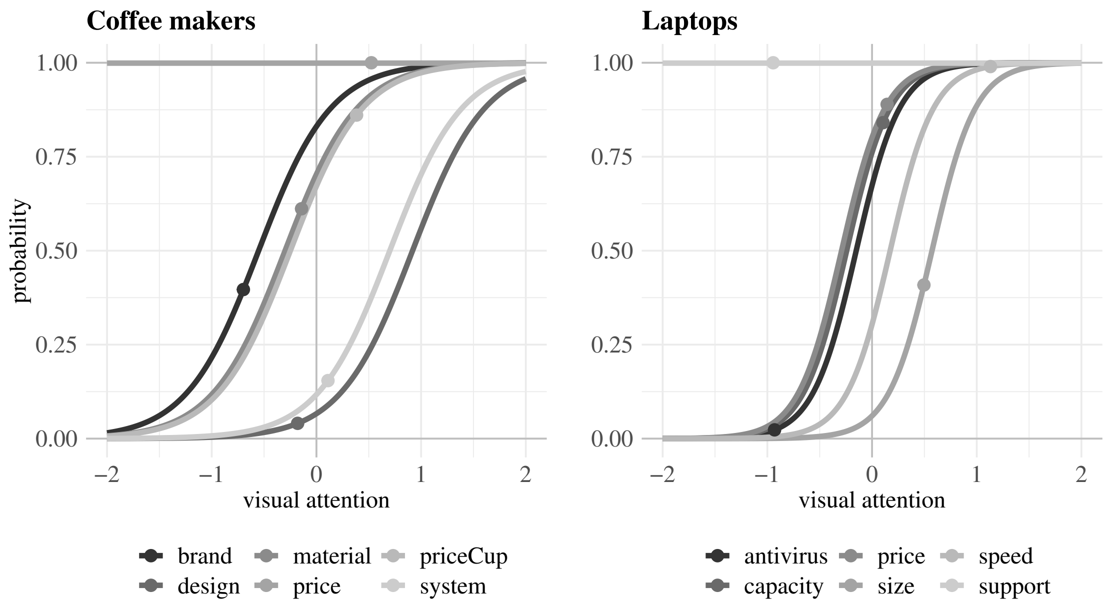
majority attending to four out of six attributes. It is, however, noteworthy that despite incentive alignment, some respondents did not attend to *price*.

Returning to the comparison of the MEAA(va) and MEAA models, some differences are visible in the attendance probabilities for *price per cup* in the coffee maker study, where the MEAA(va) model retrieves and attendance probability that is lower by 12.3 percentage points. Likewise, for laptops, we find attendance probabilities that are 7.5 to 15.6 percentage points lower for *capacity*, *size*, and *price*. As a result, the share of the respondents attending to three (four) attributes in the coffee maker (laptop) study becomes larger, mainly on account of the smaller share of those attending to five or six attributes. All in all, we find ample evidence for ANA in both product categories, frequent use of semicompensatory (more than 98%), rare use of lexicographic (0-2%) and full compensatory strategy (less than 1%), and no use of random choice. Due to the better fit and potential issues with confounding, from this point on, we focus on the heterogeneous models.

4.4.4 Visual Attention and Attribute Non-attendance

The relationship between visual attention and attribute (non)attendance merits a more detailed discussion. All in all, paying more attention to an attribute increases the likelihood of, but does not guarantee its use when making choices. Moreover, while we observe positive slopes, due to variation in attribute intercepts, the same amount of visual attention results in different attendance probabilities across attributes, as illustrated in Figure 4.3.

Here, we have calculated the attendance probabilities for a range of values of visual attention (observed in the datasets) using the estimated $\hat{\gamma}$ parameters. The positive (negative) values of attribute intercepts shift this sigmoid relationship to the left (right), such that for a given amount of visual attention (e.g., 0), a higher attendance probability is implied for *brand*, followed by *material*, *price per cup*, *system*, and *design* for coffee makers (left panel). Please note that we only have a horizontal line for *price*, as it is always attended. Importantly, the intercepts are not only affected by the relevance of the attributes for the decision-making but may also confound with other effects such as, e.g., presentation format. In particular, the attributes in the coffee maker study vary in size, color, and type of information (numeric, text, or pictorial), which may affect the amount of attention they receive (e.g., Milosavljevic et al. 2012). Due to the differences in the intercepts, the lowest (highest) values of visual attention on a given attribute across respondents (represented as dots in Figure 4.3) do not necessarily lead to the lowest (highest) attendance probabilities. For example, *brand* has the lowest average value of visual attention (-0.7) but a higher attendance probability than *system* or *design*, which receive a moderate amount of visual attention. However, even in the laptop study, which uses a standardized presentation format, we still observe substantial heterogeneity across attributes. Moreover, the slopes are steeper in comparison to the coffee maker study and this is potentially due to incentive alignment, which



Notes: points respresent the mean visual attention for a given attribute.

Figure 4.3. Effect of visual attention on attribute attendance probability (MEAA(va)) models

induces respondents to pay more attention to relevant information and be more consistent in their behavior (Yang et al. 2018) as well as a standardized presentation format. Both may subsequently lead to a less noisy measure of visual attention and therefore, a larger effect size.

4.4.5 Differences in Class Allocation

We now turn to the comparison of the MEAA models to investigate how much the visual attention measure helps with allocating people into classes. To this end, we compare the entropy measure calculated in Equation (4.7). We obtain values of 0.66 (0.76) in the MEAA model and 0.75 (0.84) in the MEAA(va) model in the coffee maker (laptop) study. Considering 32 classes in both applications, the class allocation already appears to be quite good in the MEAA model and even more so in the MEAA(va) model. To illustrate some general patterns and critical distinctions between the models, we report an example of class allocation for two respondents in the coffee maker study in Figure 4.4. However, these are representative for most of the respondents in the analyses (64% and 70% in the coffee maker and laptop studies, respectively), where the MEAA(va) model compared to the MEAA model has a higher posterior probability for the identified class.

More specifically, id = 14 (top panel) represents the case (34% and 26% in the coffee maker and laptop studies, respectively) where the MEAA(va) and the MEAA models indicate the same class, but the former results in a higher posterior probability. By contrast, id = 28 (bottom panel) illustrates the case (30% and 44% in coffee maker and laptop studies, respectively), where the class allocation is different, with the MEAA(va) model having a higher posterior probability for

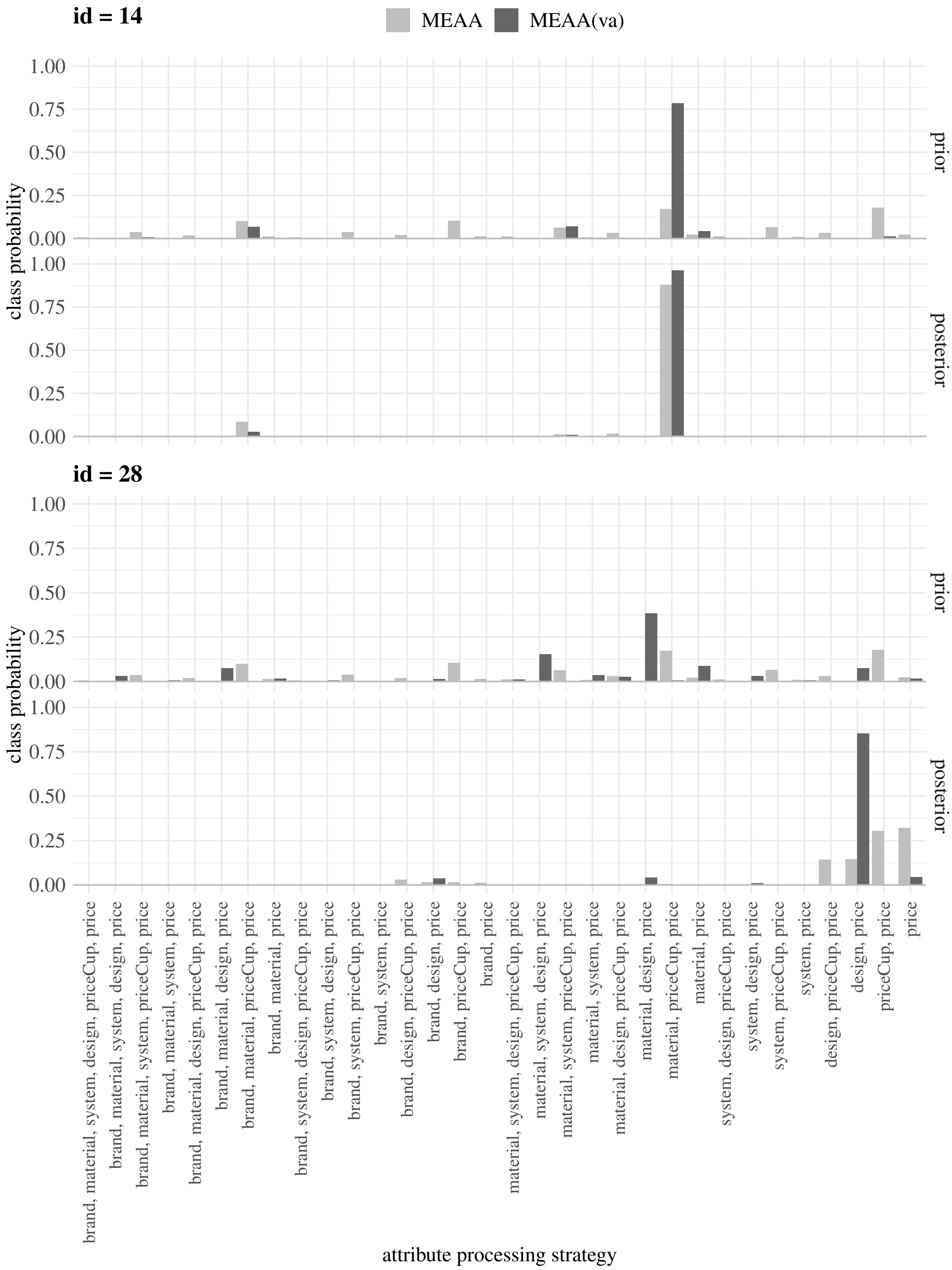


Figure 4.4. Class allocation based on the MEAA and MEAA(va) models for selected individuals in the coffee maker study

the identified class. As the classes are distinct in terms of the implied attribute processing strategy, differences in the class allocation will have consequences for other individual-level measures. For instance, the MEAA(va) model suggests that id = 28, in addition to *price* (which is always attended), most likely attends to *design*. In contrast, the MEAA model suggests that this respondent only attends to *price* and potentially to *price per cup*. Therefore, the vector of parameters for id

= 28 would be considerably different between the models, which will have further repercussions for the WTP. Given that the models suggest different class allocations (irrespective of which model leads to a higher posterior class probability) for a considerable proportion of the samples (47% and 67% in the coffee maker and laptop studies, respectively), one can expect substantial discrepancies between the derived individual-level insights. Hence, the additional use of visual attention is not only important to improve (in-sample) fit on the aggregate level but also to obtain substantive results on the individual level, which in turn are relevant for target marketing.

4.4.6 Relative Importance of Attributes and Willingness-to-pay

The aggregate values of the relative importance of attributes for both studies are summarized in Table 4.5. Columns 3 to 5 contain the average values for the whole sample, i.e., including individuals who do not attend to an attribute and therefore have zero importance in the MEAA models. At first glance, the sample means seem consistent (e.g., same ranking across attributes). However, we still observe some meaningful differences in both studies. For example, for coffee makers, the importance of *design* drops approx. 4 and *price* increases approx. 6 percentage points in the model accounting for ANA. Similarly, for laptops, the MMNL model understates (overstates) the relative importance of *speed* (*antivirus*). Moreover, due to the inclusion of some individuals with ANA, the range of relative importance across attributes increases even on this aggregate level from approx. 23 (31) in the MMNL model to approx. 32 (36-37) percentage points in the MEAA and MEAA(va) models in the coffee maker (laptop) study.

However, a more important comparison is between the results in column 3 (MMNL) and columns 6 and 7 (MEAA and MEAA(va)), where the average relative importance is computed only for individuals that attend to particular attributes. As the latter implies different subsets of the sample, the sum across attributes is no longer 100%. Here, we see substantial increases in the relative importance across all attributes (except for the always attended to *price* for coffee makers and *support* for laptops). The magnitude of the difference depends on the amount of ANA for a given attribute. For instance, the importance of *design* rises from 7.8% in the MMNL model to approx. 32% in the MEAA and MEAA(va) models. Contrasting with the results of Gilbride et al. (2006), we find larger differences in the relative importance measure, implying that these differences are context-specific.

Furthermore, the difference between the MEAA and MEAA(va) models appears to be less pronounced but still meaningful for practitioners. Even the mean sample values (columns 4 and 5) differ by approx. 2 to 3 percentage points for *price per cup* for the coffee maker study and *speed* and *price* for the laptop study. For the subsets of attenders (columns 6 and 7), we find approx. 2 and 5 percentage point differences

			Mean across all respondents		Mean across attenders only	
Data set	**Attribute**	**MMNL**	**MEAA**	**MEAA(va)**	**MEAA**	**MEAA(va)**
Coffee makers	Brand	9.2%	6.8%	8.0%	23.7%	21.5%
	Material	16.6%	16.3%	15.9%	32.0%	30.2%
	System	10.5%	8.1%	8.8%	30.0%	30.5%
	Design	7.8%	3.8%	4.4%	32.4%	32.2%
	Price per cup	25.1%	28.5%	25.7%	30.6%	35.3%
	Price	30.8%	36.4%	37.3%	36.4%	37.3%
Laptops	Speed	35.4%	37.9%	39.9%	39.6%	43.0%
	Size	15.0%	13.6%	14.6%	25.7%	30.1%
	Capacity	19.9%	19.6%	18.4%	24.9%	27.5%
	Support	4.0%	3.5%	3.4%	3.5%	3.4%
	Antivirus	4.2%	2.2%	2.7%	30.4%	37.8%
	Price	21.5%	23.2%	21.0%	23.2%	34.9%

Table 4.5. Average relative importance of attributes

for *brand* and *price per cup* for coffee makers and even larger differences of approx. 7 and 12 percentage points for *antivirus* and *price* for laptops, respectively.

The implied WTP across the three models, presented in Table 4.6, also varies.[8] In additiona, for the MEAA and MEAA(va) models, we report the sample mean (columns 3 and 4) and the mean across the individuals attending to an attribute (columns 5 and 6).

For most of the attribute-level comparisons, the MMNL model seems to overestimate the average WTP (columns 2-4). While in some cases the differences appear to be small (e.g., for Krups vs. Severin 22.10€ in the MMNL model compared to 18.98€ and 20.45€ in the MEAA and MEAA(va) models, respectively), in other cases they are considerable (e.g., for Philips vs. Severin 43.50€ in the MMNL model vs. 23€ and 22.73€ in the MEAA and MEAA(va) models, respectively). This finding is in line with the studies of Hole et al. (2013) and Hess et al. (2013). As 38.4% of the sample in the MEAA model and 40.2% in the MEAA(va) model ignore the brand, they, subsequently have a zero WTP, which decreases the average value over the sample. By contrast, when we consider only the subsets of attenders to the specific attribute (columns 5 and 6), the MMNL model understates the WTP across almost all attribute-level comparisons by more than two times. Interestingly, the MEAA(va) model shows here (in absolute terms) slightly lower WTP values (except for stainless steel vs. aluminum) compared to the MEAA model.

To obtain a better understanding of the individual-level differences, we present the cumulative distribution of individual WTP values (see also Hensher et al.

[8] As the laptop study did not include a “none” option, we do not present the WTP calculations, as WTP values are not necessarily meaningful (Allenby et al. 2014). Nevertheless, the general patterns observed for coffee makers are also present in the laptop study. The results are available upon request.

		Mean across all respondents		Mean across attenders only	
Attribute	**MMNL**	**MEAA**	**MEAA(va)**	**MEAA**	**MEAA(va)**
Brand: Braun vs. Severin	28.98€	20.99€	21.51€	72.83€	57.67€
Brand: Krups vs. Severin	22.10€	18.98€	20.45€	65.87€	54.83€
Brand: Philips vs. Severin	43.50€	23.00€	22.73€	79.83€	60.94€
Material: Stainless steel vs. Aluminum	55.42€	23.61€	25.04€	46.44€	47.66€
Material: Plastic vs. Aluminum	-25.42€	-27.63€	-24.84€	-54.33€	-47.27€
System: Pad vs. Capsule	28.81€	29.79€	30.25€	109.85€	105.00€
Design: A vs. D	-33.56€	-10.40€	-9.97€	-87.61€	-73.50€
Design: B vs. D	-7.68€	-0.96€	-0.84€	-8.10€	-6.17€
Design: C vs. D	0.54€	3.88€	4.11€	32.67€	30.30€

Table 4.6. Average willingness-to-pay for coffee makers

2013) for selected attribute-level comparisons in Figure 4.5. The Krups vs. Severin comparison (upper panel) is representative for 6 of 9 attribute-level comparisons, where the WTP stays (mostly) in the positive domain (i.e., for all individuals with nonzero WTP, Krups is preferred over Severin). By contrast, plastic vs. aluminum (lower panel) represents the other three cases, where the WTP in the MMNL model spreads across both positive and negative domains (i.e., some individuals prefer plastic over aluminum and vice versa).

In line with the previous literature (e.g., Hess et al. 2013), the MEAA and MEAA(va) models in all attribute-level comparisons suggest a lower level of heterogeneity (i.e., the variance in the WTP distribution). For both datasets, the recovered heterogeneity in WTP is overstated in the MMNL model, and it seems to be driven mainly by extremes, for which we obtain (in absolute terms) unrealistically high WTP values (e.g., |WTP| > 100€ for plastic vs. aluminum). At the same time, the WTP for the rest shrinks towards zero (e.g., |WTP| of only approx. 10 to 20€ for a large fraction of the sample). By contrast, due to a high level of non-attendance to *brand* and *material*, many individuals in the MEAA and MEAA(va) models have WTP values of exactly zero, and therefore we obtain a lower mean value over the sample. However, for the rest of the subset, the WTP values are in many cases much higher than the MMNL model predicts. Hence, consistent with Gilbride et al. (2006), we also find evidence that accounting for ANA is crucial for accurate identification of subsets of individuals with high (but realistic) WTP, i.e., the extremes of the preference distribution, and the proper targeting of these segments following the suggestions of Allenby and Ginter (1995). Comparing the WTP distributions of the MEAA and MEAA(va) models, we see that the main difference in WTP stems from different subsets of individuals with a (non)zero WTP for a given attribute, as already discussed in section 4.4.5. Note

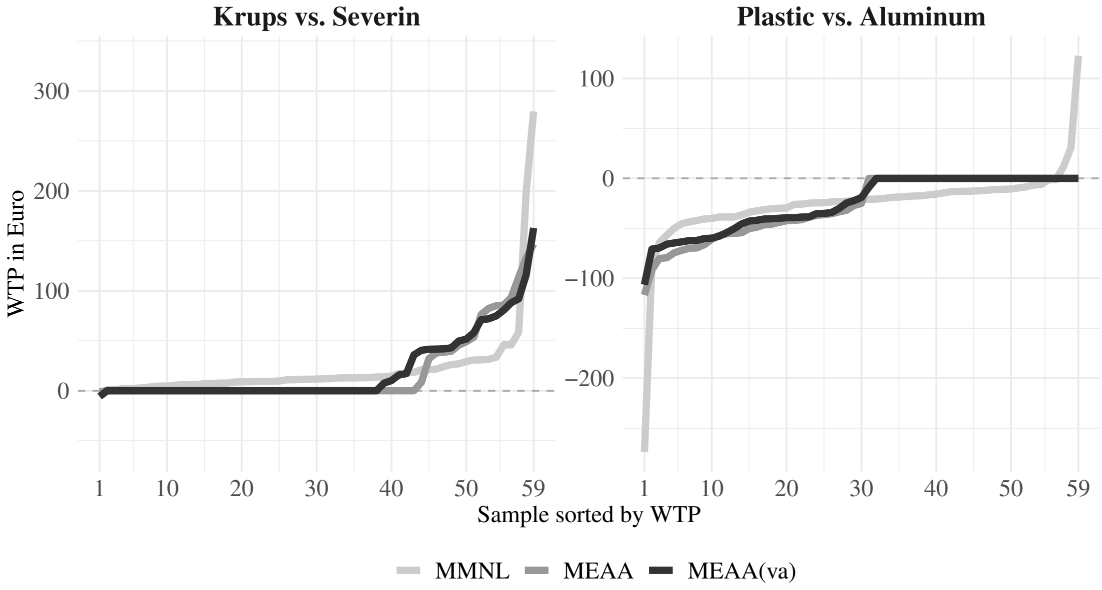


Figure 4.5. Cumulative willingness-to-pay distribution of selected attribute level comparisons for coffee makers

that, e.g., the MEAA(va) model identifies more respondents with WTP values of approx. 20€ to 50€ for Krups vs. Severin. Given that the MEAA(va) model provides better class allocation and better model fit, we interpret the resulting differences in WTP as important. Nevertheless, the WTP distributions of the models with ANA are in general similar, and larger differences arise in comparison to the MMNL model.

In sum, we conclude that it is crucial to control for heterogeneity and ANA in discrete choice models to obtain relative importance and WTP values that are realistic as well as meaningful and, at the same time, insightful for targeting in marketing applications.

4.4.7 Optimal Price

To further investigate the differences in the managerial implications derived from the models, we conduct a price optimization exercise. We develop a hypothetical choice scenario for coffee makers in which consumers choose between four brands and a none option (see Table 4.7). We focus on Severin as the focal brand of the analysis. While according to all models it offers the lowest (brand) utility (see Table 4.3), we are interested in whether it can gain a good position by differentiating on design (C) and material (stainless steel) unique to the market and what the optimal price for this product would be. For the analysis, we use the conditional individual-level estimates again and focus on the three models with preference heterogeneity (i.e., MMNL, MEAA, and MEAA(va)). The implied market shares (for all models) across the four brands are between (approx.) 10% and 30% and suggest no dominating market leader and a reasonable level of approx. 20% for opting out. Therefore, changing the price of Severin can lead to substitution within and outside the category, which is crucial for meaningful price calculations. Interestingly, although the aggregate market share predictions across the models are relatively similar, there are still differences between the MMNL and the MEAA and MEAA(va) models of approx. a few percentage points. In sum, we believe that this market scenario with clearly differentiated alternatives is suitable for an interesting price optimization task and contributes to a better understanding of the models.

We optimize the profit of Severin under the assumption of costs per unit of 97€ (approx. 2/3 of the price) for prices between 100€ and 200€, and the resulting profit-maximizing prices for the three models are 145€ (MMNL), 159€ (MEAA), and 155€ (MEAA(va)). Hence, the models give different recommendations to the manager: while the MMNL model suggests decreasing the initial price (by 4€), both models accounting for ANA, the MEAA and MEAA(va) models, advocate price increases (10€ and 6€ respectively). Furthermore, the models' optimal profits per unit differ (12.25€, 15.54€, and 15.31€ for the MMNL, MEAA, and MEAA(va) models, respectively). Assuming the best-fitting MEAA(va) model to be the "true" data-generating process and using the optimal prices from the MMNL model (e.g., using $price^{*}_{MMNL}$ in the profit function of the MEAA(va) model) leads to a missed profit opportunity of approx. 3%.

Please note, that the results should not be interpreted as that the MEAA and MEAA(va) models necessarily lead to higher optimal prices. However, our price optimization exercise shows that accounting for ANA can lead to different implications, and hence managers should consider using the proposed models.

4.5 Conclusion

In this paper, we show the prevalence of ANA in a marketing context, specifically in two applications where individuals choose durable products, such as coffee makers and laptops. Although one would expect that people are more careful when making product choices in durable categories due to higher stakes, we find that across the two applications, even after controlling for preference heterogeneity, the majority attends to only three to four (different) attributes out of the available six. Simultaneously, only a small fraction considers all the attributes, no attributes or only one attribute. In such cases, assuming full attendance can be misguided and lead to considerable biases in the derived implications.

Furthermore, we provide empirical evidence of the positive and significant effect of visual attention on the probability of attending a particular attribute. Our proposed model may further capture effects that stream from the presentation format of the attributes and choice tasks in general, and therefore provides a framework

Attribute	Alt. 1	Alt. 2	Alt. 3	Alt. 4	Alt. 5
Brand	Braun	Krups	Philips	Severin	
Material	Plastic	Aluminum	Plastic	Stainless steel	
System	Pad	Pad	Pad	Pad	None
Design	B	A	D	C	
Price per cup	20 cents	24 cents	22 cents	25 cents	
Price	129€	149€	139€	149€	

Table 4.7. Hypothetical choice scenario

for testing how changes in presentation format affect attention, attendance, and subsequently choice in CBC studies. In particular, Jonker et al. (2018) find that people attend to more attributes when color-coding the background of the attribute information is used (while keeping the size and color of the textual description of the attribute the same), but do not investigate the role of visual attention. The eye tracking literature, however, finds that the visual attention to and ease of processing of the information may depend on its visual characteristics such as size or color (e.g., Orquin and Loose 2013, Wedel and Pieters 2008). In our proposed framework, saliency manipulations may, therefore, increase the attendance probabilities through a shift in the intercepts to the left in Figure 4.3, a simple increase in the visual attention, or a combination of both.

Notably, we show that the use of eye tracking to augment the ANA models is informative in uncovering individual-level behavior. In particular, it helps to more clearly classify individuals into segments related to different attribute processing strategies. This implies less uncertainty in identifying the size of the segments that the firm might want to target and differences in the individual-level results (e.g., WTP). However, the model using the observed choices to infer ANA may already be sufficient for recovering the approximate patterns of attribute processing strategies as well as some key aggregate measures of interest (e.g., choice share predictions, relative importance and distributional characteristics of WTP).

Building upon our findings, several implications are noteworthy for marketing practitioners. We have demonstrated that ANA is plausible and applied by consumers in choice situations and that there is much to gain from employing appropriate tools to account for such behavior for segmentation, targeting, and pricing decisions. First, even on an aggregate level, models accounting for ANA lead to different results. The models fit the data better, and the distributions for parameters as well as WTP values are more plausible and realistic. As a consequence, optimal (i.e., profit-maximizing) pricing decisions may depend on the model employed by the decision maker, and ignoring ANA, result in untapped profit opportunities. Second, because of ANA the preference distribution of consumers is a mixture of zero and nonzero preferences and is crucial for marketing managers to distinguish when making decisions related to product attributes (e.g., product line extensions or new product design). The relative importance and typically WTP of attributes are higher for attenders in ANA models compared to the average values based on the MMNL model, particularly if the fraction of ANA is high (e.g., system and design for coffee makers). Hence, when firms try to differentiate their products on such attributes, it is essential to focus on the appropriate segment (i.e., consumers with attribute attendance) instead of the whole population. On the other hand, if firms are rather weak in a specific attribute, e.g., brand, they should choose to target the segments that do not attend to brand as an attribute, as they have higher chances of gaining a better position in those segments. Third, using eye tracking as auxiliary information in models accounting for ANA leads to substantively different and more certain allocation of individuals into classes that describe specific attribute processing strategies and corresponding individual-level WTP measures. Hence, considering the general trend of decreasing prices for eye tracking (Wedel 2018), our proposed model, which retains a simple way of using this information, can be valuable for practitioners that want to engage in one-to-one marketing.

We see several limitations and potential extensions of the employed model. First, we have used the eye tracking information as a proxy for visual attention. However, it can instead be modeled as an outcome of an underlying latent process to avoid potential measurement error (which we would expect only to strengthen the effect of visual attention). Second, the model can be extended by relaxing the assumption of stability in applied attribute processing strategies across choice tasks. Several questions merit further investigation: whether such switching occurs and to what extent, whether the potential biases are substantial or assuming the stability of ANA strategies is acceptable. Third, while we focus on ANA, some (subsets of) attributes may also be used for screening alternatives, which leads to heterogeneous consideration sets. Model extension to account for both possibilities can permit the investigation of additional sources of heterogeneity across individuals and merits future consideration. Last, the model can be easily extended to incorporate, e.g., alternative specifications of parameter distributions (e.g., lognormal vs. normal), and attribute-specific slopes for the effect of visual attention on attendance probabilities.

Additionally, contrasting respondents' self-reported (stated) ANA measures with our "revealed" measure from eye tracking might be interesting. Both work well in isolation (see Hole et al. 2013 for stated ANA and this paper for visual attention from eye tracking), but the question remains which of the measures is a more appropriate indicator of ANA. Furthermore, Balcombe et al. (2015), using a different modeling framework, suggest that these two measures might be complementary.

Due to the flexibility of the MEAA model, both can be simultaneously incorporated to test related hypotheses, which we leave for future research.

References

Acland, D. and Levy, M. R. (2015). Naiveté, projection bias, and habit formation in gym attendance. *Management Science*, 61(1):146–160.

Adaval, R. and Wyer, R. J. (2011). Conscious and nonconscious comparisons with price anchors: Effects on willingness to pay for related and unrelated products. *Journal of Marketing Research*, 48(2):355–365.

Agarwal, S., Driscoll, J. C., Gabaix, X., and Laibson, D. (2013). Learning in the credit card market. Available at SSRN: https://ssrn.com/abstract=1091623 or https://dx.doi.org/10.2139/ssrn.1091623.

Ailawadi, K. L., Gedenk, K., Langer, T., Ma, Y., and Neslin, S. A. (2014). Consumer response to uncertain promotions: An empirical analysis of conditional rebates. *International Journal of Research in Marketing*, 31(1):94–106.

Akerlof, G. A. (1991). Procrastination and obedience. *The American Economic Review*, 81(2):1–19.

Alemu, M. H., Morkbak, M. R., Olsen, S. B., and Jensen, C. L. (2013). Attending to the reasons for attribute non-attendance in choice experiments. *Environmental and Resource Economics*, 54(3):333–359.

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'ecole americaine. *Econometrica: Journal of the econometric society*, 21(4):503–546.

Allenby, G. M., Arora, N., and Ginter, J. L. (1998). On the heterogeneity of demand. *Journal of Marketing Research*, 35(3):384–389.

Allenby, G. M., Brazell, J. D., Howell, J. R., and Rossi, P. E. (2014). Economic valuation of product features. *Quantitative Marketing and Economics*, 12(4):421–456.

Allenby, G. M. and Ginter, J. L. (1995). Using extremes to design products and segment markets. *Journal of Marketing Research*, 32(4):392–403.

Allenby, G. M. and Rossi, P. E. (1998). Marketing models of consumer heterogeneity. *Journal of Econometrics*, 89(1):57–78.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., and Yang, H. (2018). Consumer choice and autonomy in the age of artificial intelligence and big data. *Customer Needs and Solutions*, 5:28–37.

Andrews, J. C., Netemeyer, R. G., and Burton, S. (1998). Consumer generalization of nutrient content claims in advertising. *Journal of Marketing*, 62(4):62–75.

Argo, J. J., Dahl, D. W., and Morales, A. C. (2008). Positive consumer contagion: Responses to attractive others in a retail context. *Journal of Marketing Research*, 45(4):690–701.

Ariely, D. and Loewenstein, G. (2006). The heat of the moment: The effect of sexual arousal on sexual decision making. *Journal of Behavioral Decision Making*, 19(2):87–98.

Balasubramanian, S. K. and Cole, C. (2002). Consumers' search and use of nutrition information: The challenge and promise of the nutrition labeling and education act. *Journal of Marketing*, 66(3):112–127.

Balcombe, K., Fraser, I., and McSorley, E. (2015). Visual attention and attribute attendance in multi-attribute choice experiments. *Journal of Applied Econometrics*, 30(3):447–467.

Barberis, N. and Thaler, R. (2003). Chapter 18: A survey of behavioral finance. In *Financial Markets and Asset Pricing*, volume 1 of *Handbook of the Economics of Finance*, pages 1053–1128. Elsevier.

Berger, J. and Fitzsimon, G. (2008). Dogs on the street, pumas on your feet: How cues in the environment influence product evaluation and choice. *Journal of Marketing Research*, 45(1):1–14.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., and Schweidel, D. A. (2019). Uniting the tribes: Using text for marketing insight. *Journal of Marketing*, forthcoming.

Berger, J. and Iyengar, R. (2013). Communication channels and word of mouth: How the medium shapes the message. *Journal of Consumer Research*, 40(3):567–579.

Bettman, J. R., Luce, M. F., and Payne, J. W. (1998). Constructive consumer choice processes. *Journal of Consumer Research*, 25(3):187–217.

Brasel, S. A. and Gips, J. (2014). Tablets, touchscreens, and touchpads: How varying touch interfaces trigger psychological ownership and endowment. *Journal of Consumer Psychology*, 24(2):226–233.

Bronnenberg, B. J. and Vanhonacker, W. R. (1996). Limited choice sets, local price response and implied measures of price competition. *Journal of Marketing Research*, 33(2):163–173.

Bruno, H. A., Che, H., and Dutta, S. (2012). Role of reference price on price and quantity: Insights from business-to-business markets. *Journal of Marketing Research*, 49(5):640–654.

Brynjolfsson, E. and Smith, M. D. (2000). Frictionless commerce? a comparison of internet and conventional retailers. *Management Science*, 46(4):563–585.

Buchheim, L. and Kolaska, T. (2016). Weather and the psychology of purchasing outdoor movie tickets. *Management Science*, 63(11):3718–3738.

Burda, M., Harding, M., and Hausman, J. (2008). A bayesian mixed logit – probit model for multinomial choice. *Journal of Econometrics*, 147(2):232–246.

Busse, M. R., Pope, D. G., Pope, J. C., and Silva-Risso, J. (2012). Projection bias in the car and housing markets. Working Paper 18212, National Bureau of Economic Research. Available at http://www.nber.org/papers/w18212.

Busse, M. R., Pope, D. G., Pope, J. C., and Silva-Risso, J. (2015). The psychological effect of weather on car purchases. *The Quarterly Journal of Economics*, 130(1):371–414.

Cain, D. M., Loewenstein, G., and Moore, D. A. (2005). The dirt on coming clean: Perverse effects of disclosing conflicts of interest. *The Journal of Legal Studies*, 34(1):1–25.

Camerer, C. and Lovallo, D. (1999). Overconfidence and excess entry: An experimental approach. *American Economic Review*, 89(1):306–318.

Camerer, C. and Thaler, R. H. (1995). Anomalies: Ultimatums, dictators and manners. *The Journal of Economic Perspectives*, 9(2):209–219.

Campbell, M. C. (1999). Perceptions of price unfairness: Antecedents and consequences. *Journal of Marketing Research*, 36(2):187–199.

Chandon, P., Hutchinson, J. W., Bradlow, E. T., and Young, S. H. (2009). Does in-store marketing work? Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase. *Journal of Marketing*, 73(6):1–17.

Chark, R. and Muthukrishnan, A. (2013). The effect of physical possession on preference for product warranty. *International Journal of Research in Marketing*, 30(4):424–425.

Cheema, A. and Patrick, V. M. (2008). Anytime versus only: Mind-sets moderate the effect of expansive versus restrictive frames on promotion evaluation. *Journal of Marketing Research*, 45(4):462–472.

Chernev, A., Böckenholt, U., and Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, 25(2):333–358.

Christopher, R. M. and Machado, F. S. (2019). Consumer response to design variations in pay-what-you-want pricing. *Journal of the Academy of Marketing Science*, 47:879–898.

Chung, K. (2019). Incorporating a "better" behavioral bias for both consumers and firms in rebate programs. *Management Science*, forthcoming.

Collins, A. T. (2012). *Attribute nonattendance in discrete choice models: measurement of bias, and a model for the inference of both nonattendance and taste heterogeneity*. PhD dissertation, Institute of Transportation and Logistics Studies, University of Sydney Business School.

Collins, A. T., Rose, J. M., and Hensher, D. A. (2013). Specification issues in a generalised random parameters attribute nonattendance model. *Transport Research Part B: Methodological*, 56:234–253.

Conick, H. (2017). Read this story to learn how behavioral economics can improve marketing. Retrieved from https://www.ama.org/publications/MarketingNews/Pages/read-story-learn-how-behavioral-economics-can-improve-marketing.aspx.

Conlin, M., O'Donoghue, T., and Vogelsang, T. J. (2007). Projection bias in catalog orders. *The American Economic Review*, 97(4):1217–1249.

Cowley, E. (2006). Processing exaggerated advertising claims. *Journal of Business Research*, 59(6):728–734.

Cox, A. D. and Cox, D. (1990). Competing on price: The role of retail price advertisements in shaping store-price image. *Journal of Retailing*, 66(4):428–445.

Cox, D. and Cox, A. D. (2001). Communicating the consequences of early detection: The role of evidence and framing. *Journal of Marketing*, 65(3):91–103.

Currim, I. S., Mintz, O., and Siddarth, S. (2015). Information accessed or information available? The impact on consumer preferences inferred at a durable product e-commerce website. *Journal of Interactive Marketing*, 29:11–25.

Dadwal, S. S. and Hassan, A. (2015). The augmented reality marketing: A merger of marketing and technology in tourism. In Ray, N., editor, *Emerging Innovative Marketing Strategies in the Tourism Industry*, pages 78– 96. IGI Global.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market under– and overreactions. *The Journal of Finance*, 53:1839–1885.

Dayton, C. M. and Macready, G. B. (1988). Concomitant-variable latent-class models. *Journal of the American Statistical Association*, 83(401):173–178.

Dellaert, B. G., Donkers, B., and Van Soest, A. (2012). Complexity effects in choice experiment-based models. *Journal of Marketing Research*, 49(3):424–434.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2):315–372.

DellaVigna, S. (2018). Structural behavioral economics. Working Paper 24797, National Bureau of Economic Research. Available at https://www.nber.org/papers/w24797.pdf.

DellaVigna, S., List, J. A., and Malmendier, U. (2012). Testing for altruism and social pressure in charitable giving. *The Quarterly Journal of Economics*, 127(1):1–56.

DellaVigna, S. and Malmendier, U. (2006). Paying not to go to the gym. *The American Economic Review*, 96(3):694–719.

Desarbo, W. S., Ramaswamy, V., and Cohen, S. H. (1995). Market segmentation with choice-based conjoint analysis. *Marketing Letters*, 6(2):137–147.

Dhami, S. (2016). *Judgment Heuristics. The Foundations of Behavioral Economic Analysis*. Oxford University Press, New York.

Dhar, R. (1997). Context and task effects on choice deferral. *Marketing Letters*, 8(1):119–130.

Dhar, R., Nowlis, S. M., and Sherman, S. J. (2000). Trying hard or hardly trying: An analysis of context effects in choice. *Journal of Consumer Psychology*, 9(4):189–200.

Dhar, R. and Simonson, I. (2003). The effect of forced choice on choice. *Journal of Marketing Research*, 40(2):146–160.

Dickson, P. R. and Sawyer, A. G. (1990). The price knowledge and search of supermarket shoppers. *Journal of Marketing*, 54(3):42–53.

Diehl, K. (2005). When two rights make a wrong: Searching too much in ordered environments. *Journal of Marketing Research*, 42(3):313–322.

Ding, M., Eliashberg, J., Huber, J., and Saini, R. (2005). Emotional bidders—an analytical and experimental examination of consumers' behavior in a priceline-like reverse auction. *Management Science*, 51(3):352–364.

Dowling, K., Guhl, D., Klapper, D., Spann, M., Stich, L., and Yegoryan, N. (2020). Behavioral biases in marketing. *Journal of the Academy of Marketing Science*, 48:449–477.

Dowling, K., Manchanda, P., and Spann, M. (2018). The existence and persistence of the pay-per-use bias in car sharing services. Available at SSRN: https://ssrn.com/abstract=3204233.

Draganska, M. and Jain, D. C. (2006). Consumer preferences and product-line pricing strategies: An empirical analysis. *Marketing Science*, 25(2):164–174.

Draganska, M. and Klapper, D. (2011). Choice set heterogeneity and the role of advertising: An analysis with micro and macro data. *Journal of Marketing Research*, 48(4):653–669.

Dubé, J.-P., Hitsch, G. J., and Jindal, P. (2014). The joint identification of utility and discount functions from stated choice data: An application to durable goods adoption. *Quantitative Marketing and Economics*, 12(4):331–377.

Dubé, J.-P., Luo, X., and Fang, Z. (2017). Self-signaling and prosocial behavior: A cause marketing experiment. *Marketing Science*, 36(2):161–186.

Eckhardt, G. M., Houston, M. B., Jiang, B., Lamberton, C., Rindfleisch, A., and Zervas, G. (2019). Marketing in the sharing economy. *Journal of Marketing*, 83(5):5–27.

Elshiewy, O., Guhl, D., and Boztuğ, Y. (2017). Multinomial logit models in marketing – from fundamentals to state-of-the-art. *Marketing ZFP*, 39(3):32–49.

Erdem, T. (1996). A dynamic analysis of market structure based on panel data. *Marketing Science*, 15(4):359–378.

Fehr, E. and Gächter, S. (2000). Fairness and retaliation: The economics of reciprocity. *The Journal of Economic Perspectives*, 14(3):159–181.

Fehr, E. and Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics*, 114(3):817–868.

Fosgerau, M., Melo, E., and Shum, M. (2016). Discrete choice and rational inattention: A general equivalence result. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2889048.

Frischknecht, B. D., Eckert, C., Geweke, J., and Louviere, J. J. (2014). A simple method for estimating preference parameters for individuals. *International Journal of Research in Marketing*, 31(1):35–48.

Gardete, P. M. (2015). Social effects in the in-flight marketplace: Characterization and managerial implications. *Journal of Marketing Research*, 52(3):360–374.

Gershoff, A. D., Kivetz, R., and Keinan, A. (2012). Consumer response to versioning: How brands' production methods affect perceptions of unfairness. *Journal of Consumer Research*, 39(2):382–398.

Ghose, A., Goldfarb, A., and Han, S. P. (2013). How is the mobile internet different? search costs and local activities. *Information Systems Research*, 24(3):613–631.

Gilbert, D. T., Pinel, E. C., Wilson, T. D., Blumberg, S. J., and Wheatley, T. P. (1998). Immune neglect: A source of durability bias in affective forecasting. *Journal of Personality and Social Psychology*, 75(3):617–628.

Gilbride, T. J., Allenby, G. M., and Brazell, J. D. (2006). Models for heterogenous variable selection. *Journal of Marketing Research*, 43(3):420–430.

Gilbride, T. J. and Lenk, P. J. (2010). Posterior predictive model checking: An application to multivariate normal heterogeneity. *Journal of Marketing Research*, 47(5):896–909.

Gilovich, T., Vallone, R., and Tversky, A. (1985). The hot hand in basketball: on the misperception of random sequences. *Cognitive Psychology*, 17:295–314.

Glasgow, G. and Butler, S. (2017). The value of non-personally identifiable information to consumers of online services: evidence from a discrete choice experiment. *Applied Economics Letters*, 24(6):392–395.

Glöckner, A. and Betsch, T. (2008). Multiple-reason decision making based on automatic processing. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 34(5):1055–1075.

Gneezy, A., Gneezy, U., and Lauga, D. O. (2014). A reference-dependent model of the price–quality heuristic. *Journal of Marketing Research*, 51(2):153–164.

Goldsmith, K. and Amir, O. (2010). Can uncertainty improve promotions? *Journal of Marketing Research*, 47(6):1070–1077.

Goodman, J. K. and Irmak, C. (2013). Having versus consuming: Failure to estimate usage frequency makes consumers prefer multifeature products. *Journal of Marketing Research*, 50(1):44–54.

Goukens, C., Dewitte, S., Pandelaere, M., and Warlop, L. (2007). Wanting a bit(e) of everything: Extending the valuation effect to variety seeking. *Journal of Consumer Research*, 34(3):386–394.

Grewening, E., Lergetporer, P., Werner, K., and Smarzynska Javorcik, B. (2019). Incentives, search engines, and the elicitation of subjective beliefs: Evidence from representative online survey experiments. Working Paper 7556, CESifo. Available at https://ssrn.com/abstract=3357133.

Guadagni, P. M. and Little, J. D. C. (1983). A logit model of brand choice calibrated on scanner data. *Marketing Science*, 2(3):203–238.

Guercini, S., La Rocca, A., Runfola, A., and Snehota, I. (2015). Heuristics in customer–supplier interaction. *Industrial Marketing Management*, 48:26–37.

Guha, A., Biswas, A., Grewal, D., Verma, S., Banerjee, S., and Nordfält, J. (2018). Reframing the discount as a comparison against the sale price: Does it make the discount more attractive? *Journal of Marketing Research*, 55(3):339–351.

Gupta, S. and Chintagunta, P. K. (1994). On using demographic variables to determine segment membership in logit mixture models. *Journal of Marketing Research*, 31(1):128–136.

Hagenbuch, D. J., Wiese, M. D., Dose, J. J., and Bruce, M. L. (2008). Understanding satisfied and affectively committed clients' lack of referral intent. *Services Marketing Quarterly*, 29(3):24–74.

Hainmueller, J., Hiscox, M. J., and Sequeira, S. (2015). Consumer demand for fair trade: Evidence from a multistore field experiment. *Review of Economics and Statistics*, 97(2):242–256.

Hart, O. and Moore, J. (2008). Contracts as reference points. *Quarterly Journal of Economics*, 123(1):1–48.

Hauser, J. R., Urban, G. L., Liberali, G., and Braun, M. (2009). Website morphing. *Marketing Science*, 28(2):202–223.

Hensher, D. A. (2006). How do respondents process stated choice experiments? Attribute consideration under varying information load. *Journal of Applied Econometrics*, 21(6):861–878.

Hensher, D. A. (2014). Attribute processing as a behavioural strategy in choice making. In Hess, S. and Andrew, D., editors, *Handbook of Choice Modelling*, pages 268–289. Edward Elgar Publishing, Cheltenham, UK.

Hensher, D. A., Collins, A. T., and Greene, W. H. (2013). Accounting for attribute non-attendance and common-metric aggregation in a probabilistic decision process mixed multinomial logit model: A warning on potential confounding. *Transportation*, 40(5):1003–1020.

Hensher, D. A., Rose, J., and Greene, W. H. (2005). The implications on willingness to pay of respondents ignoring specific attributes. *Transportation*, 32(3):203–222.

Hensher, D. A., Rose, J., and Greene, W. H. (2015). *Applied Choice Analysis*. Cambridge University Press, Cambridge, UK, 2 edition.

Hess, S. and Hensher, D. A. (2010). Using conditioning on observed choices to retrieve individual-specific attribute processing strategies. *Transportation Research Part B: Methodological*, 44(6):781–790.

Hess, S. and Hensher, D. A. (2013). Making use of respondent reported processing information to understand attribute importance: A latent variable scaling approach. *Transportation*, 40(2):397–412.

Hess, S., Stathopoulos, A., Campbell, D., and Caussade, S. (2013). It's not that I don't care, I just don't care very much: Confounding between attribute non-attendance and taste heterogeneity. *Transportation*, 40(3):583–607.

Hilken, T., Ruyter, K. d., Chylinski, M., Mahr, D., and Keeling, D. I. (2017). Augmenting the eye of the beholder: Exploring the strategic potential of augmented reality to enhance online service experiences. *Journal of the Academy of Marketing Science*, 45(6):884–905.

Ho, T. H., Lim, N., and Camerer, C. F. (2006). Modeling the psychology of consumer and firm behavior with behavioral economics. *Journal of Marketing Research*, 43(3):307–331.

Hole, A. R. (2011). A discrete choice model with endogenous attribute attendance. *Economic Letters*, 110(3):203–205.

Hole, A. R., Kolstad, J. R., and Gyrd-Hansen, D. (2013). Inferred vs. stated attribute non-attendance in choice experiments: A study of doctors' prescription behaviour. *Journal of Economic Behavior & Organization*, 96:21–31.

Howard, J. A. and Sheth, J. N. (1969). *The Theory of Buyer Behavior*. John Wiley & Sons, Inc, New York.

Huber, J., Payne, J. W., and Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research*, 9(1):90–98.

Huber, J. and Puto, C. (1983). Market boundaries and product choice: Illustrating attraction and substitution effects. *Journal of Consumer Research*, 10(1):31–44.

Huber, J. and Train, K. (2001). On the similarity of classical and bayesian estimates of individual mean partworths. *Marketing Letters*, 12(3):259–269.

Hui, S. K., Inman, J. J., Huang, Y., and Suher, J. (2013). The effect of in-store travel distance on unplanned spending: Applications to mobile promotion strategies. *Journal of Marketing*, 77(2):1–16.

Huyghe, E., Verstraeten, J., Geuens, M., and van Kerckhove, A. (2017). Clicks as a healthy alternative to bricks: How online grocery shopping reduces vice purchases. *Journal of Marketing Research*, 54(1):61–74.

Imai, K., Tingley, D., and Yamamoto, T. (2013). Experimental designs for identifying causal mechanisms. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 176:5–51.

Iyer, G. R., Blut, M., Xiao, S. H., and Grewal, D. (2019). Impulse buying: a meta-analytic review. *Journal of the Academy of Marketing Science*, 11(2):111.

Jain, K. and Srinivasan, N. (1990). An empirical assessment of multiple operationalizations of involvement. In Goldberg, M., Gorn, G., and Pollay, R., editors, *Advances in Consumer Research*, volume 17, pages 594–602. Association for Consumer Research, Provo, UT.

Javornik, A. (2016). "It's an illusion, but it looks real!" consumer affective, cognitive and behavioural responses to augmented reality applications. *Journal of Marketing Management*, 32:9–10.

Jindal, P. (2015). Risk preferences and demand drivers of extended warranties. *Marketing Science*, 34(1):39–58.

Johnson, J. and Tellis, G. J. (2005). Blowing bubbles: heuristics and biases in the run-up of stock prices. *Journal of the Academy of Marketing Science*, 33(4):486–503.

Johnson, J., Tellis, G. J., and Macinnis, D. J. (2005). Losers, winners, and biased trades. *Journal of Consumer Research*, 32(2):324–329.

Jonker, M. F., Donkers, B., de Bekker-Grob, E. W., and Stolk, E. A. (2018). Effect of level overlap and color coding on attribute non-attendance in discrete choice experiments. *Value in Health*, 21(7):767 – 771.

Joo, J. (2018). Rational inattention as an empirical framework: Application to the welfare effects of new-product introduction. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3182795.

Jung, M. H., Nelson, L. D., Gneezy, U., and Gneezy, A. (2017). Signaling virtue: Charitable behavior under consumer elective pricing. *Marketing Science*, 36(2):187–194.

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *The Journal of Economic Perspectives*, 5(1):193–206.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–292.

Kalra, A. and Shi, M. (2010). Consumer value-maximizing sweepstakes and contests. *Journal of Marketing Research*, 47(2):287–300.

Kalyanam, K. and Putler, D. S. (1997). Incorporating demographic variables in brand choice models: An indivisible alternatives framework. *Marketing Science*, 16(2):166–181.

Kalyanaram, G. and Winer, R. S. (1995). Empirical generalizations from reference price research. *Marketing Science*, 14(3):G161–G169.

Kamakura, W. A., Kim, B.-D., and Lee, J. (1996). Modeling preference and structural heterogeneity in consumer choice. *Marketing Science*, 15(2):152–172.

Kamakura, W. A. and Russell, G. J. (1989). A probabilistic choice model for market segmentation and elasticity structure. *Journal of Marketing Research*, 26(4):379–390.

Kamakura, W. A., Wedel, M., and Agrawal, J. (1994). Concomitant variable latent class models for conjoint analysis. *International Journal of Research in Marketing*, 11(5):451–464.

Keane, M. and Wasi, N. (2013). Comparing alternative models of heterogeneity in consumer choice behavior. *Journal of Applied Econometrics*, 28(6):1018–1045.

Kivetz, R. (2003). The effects of effort and intrinsic motivation on risky choice. *Marketing Science*, 22(4):477–502.

Kivetz, R., Netzer, O., and Srinivasan, V. (2004). Alternative models for capturing the compromise effect. *Journal of Marketing Research*, 41(3):237–257.

Kivetz, R. and Simonson, I. (2002). Self-control for the righteous: Toward a theory of precommitment to indulgence. *Journal of Consumer Research*, 29(2):199–217.

Kocher, M. G., Pahlke, J., and Trautmann, S. T. (2013). Tempus fugit : Time pressure in risky decisions. *Management Science*, 59(10):2380–2391.

Krishna, A., Briesch, R., Lehmann, D. R., and Yuan, H. (2002). A meta-analysis of the impact of price presentation on perceived savings. *Journal of Retailing*, 78(2):101–118.

Krucien, N., Ryan, M., and Hermens, F. (2017). Visual attention in multi-attributes choices: What can eye-tracking tell us? *Journal of Economic Behavior and Organization*, 135:251–267.

Lacetera, N., Pope, D. G., and Sydnor, J. R. (2012). Heuristic thinking and limited attention in the car market. *American Economic Review*, 102(5):2206–2236.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2):443–477.

Lamberton, C. and Stephen, A. T. (2016). A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry. *Journal of Marketing*, 80(6):146–172.

Lambrecht, A. and Skiera, B. (2006). Paying too much and being happy about it: Existence, causes, and consequences of tariff-choice biases. *Journal of Marketing Research*, 43(2):212–223.

Lambrecht, A. and Tucker, C. (2019). Algorithmic bias? an empirical study of apparent gender-based discrimination in the display of stem career ads. *Management Science*, 65(7):2966–2981.

Lambrecht, A. and Tucker, C. E. (2015). Field experiments in marketing. Available at SSRN: https://ssrn.com/abstract=2630209.

Larrick, R. P., Burson, K. A., and Soll, J. B. (2007). Social comparison and confidence: When thinking you're better than average predicts overconfidence (and when it does not). *Organizational Behavior and Human Decision Processes*, 102(1):76–94.

Laurent, G. and Kapferer, J.-N. (1985). Measuring consumer involvement profiles. *Journal of Marketing Research*, 22(1):41–53.

Lee, L., Inman, J. J., Argo, J. J., Böttger, T., Dholakia, U., Gilbride, T., van Ittersum, K., Kahn, B., Kalra, A., Lehmann, D. R., McAlister, L. M., Shankar, V., and Tsai, C. I. (2018). From browsing to buying and beyond: The needs-adaptive shopper journey model. *Journal of the Association for Consumer Research*, 3(3):277–293.

Lee, L., Lee, M. P., Bertini, M., Zauberman, G., and Ariely, D. (2015). Money, time, and the stability of consumer preferences. *Journal of Marketing Research*, 52(2):184–199.

Lemon, K. N. and Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6):69–96.

Levin, I. P. and Gaeth, G. J. (1988). How consumers are affected by the framing of attribute information before and after consuming the product. *Journal of Consumer Research*, 15(3):374–378.

Levin, I. P., Schneider, S. L., and Gaeth, G. J. (1998). All frames are not created equal: A typology and critical analysis of framing effects. *Organizational Behavior and Human Decision Processes*, 76(2):149–188.

Liechty, J., Pieters, R., and Wedel, M. (2003). Global and local covert visual attention: Evidence from a bayesian hidden markov model. *Psychometrika*, 68(4):519–541.

Liu, Q. and Tang, Y. E. (2015). Construction of heterogeneous conjoint choice designs: A new approach. *Marketing Science*, 34(3):346–366.

Loewenstein, G. (1988). Frames of mind in intertemporal choice. *Management Science*, 34(2):200–214.

Loewenstein, G. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, 65(3):272–292.

Loewenstein, G., O'Donoghue, T., and Rabin, M. (2003). Projection bias in predicting future utility. *The Quarterly Journal of Economics*, 118(4):1209–1248.

Loewenstein, G. and Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *The Quarterly Journal of Economics*, 107(2):573–597.

Loewenstein, G., Weber, E. U., Hsee, C. K., and Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, 127(2):267–286.

Louro, M. J., Pieters, R., and Zeelenberg, M. (2005). Negative returns on positive emotions: The influence of pride and self–regulatory goals on repurchase decisions. *Journal of Consumer Research*, 31(4):833–840.

Louviere, J. J., Hensher, D. A., and Swait, J. D. (2000). *Stated Choice Methods: Analysis and Applications*. Cambridge University Press, Cambridge, UK.

Luce, R. D. (1959). *Individual choice behavior: A theoretical analysis*. John Wiley & Sons, New York.

Maldonado, S., Montoya, R., and López, J. (2017). Embedded heterogeneous feature selection for conjoint analysis: A SVM approach using L1 penalty. *Applied Intelligence*, 46:775–787.

Maldonado, S., Montoya, R., and Weber, R. (2015). Advanced conjoint analysis using feature selection via support vector machines. *European Journal of Operational Research*, 241(2):564–574.

Malhotra, N. K. (1982). Information load and consumer decision making. *Journal of Consumer Research*, 8(4):419–430.

Malmendier, U. and Taylor, T. (2015). On the verges of overconfidence. *Journal of Economic Perspectives*, 29(4):3–8.

Matz, S. C. and Netzer, O. (2017). Using big data as a window into consumers' psychology. *Current Opinion in Behavioral Sciences*, 18:7–12.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3(4):303–328.

McFadden, D. (2001). Economic choices. *American Economic Review*, 91(3):351–378.

McFadden, D. and Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5):447–470.

McLachlan, G. J. and Peel, D. (2000). *Finite Mixture Models*. Wiley, New York.

McQuarrie, E. F. and Michael, M. J. (1986). The Zaichkowsky personal involvement inventory: Modification and extension. In Anderson, P. and Wallendorf, M., editors, *Advances in Consumer Research*, volume 14, pages 36–40. Association for Consumer Research, Provo, UT.

Mehta, N., Rajiv, S., and Srinivasan, K. (2003). Price uncertainty and consumer search: A structural model of consideration set formation. *Marketing Science*, 22(1):58–84.

Meißner, M., Musalem, A., and Huber, J. (2016). Eye tracking reveals processes that enable conjoint choices to become increasingly efficient with practice. *Journal of Marketing Research*, 53(1):1–17.

Meißner, M. and Oll, J. (2017). The promise of eye-tracking methodology in organizational research: A taxonomy, review and future avenues. *Organizational Research Methods*, 22(2):590–617.

Meißner, M., Scholz, S., and Decker, R. (2011). Using eyetracking and mouselab to examine how respondents process information in choice-based conjoint analysis. In *Proceedings of the Sawtooth Software Conference 2010*, pages 151–170.

Meloy, M. G. (2000). Mood-driven distortion of product information. *Journal of Consumer Research*, 27(3):345–359.

Meyer, R. J., Zhao, S., and Han, J. K. (2008). Biases in valuation vs. usage of innovative product features. *Marketing Science*, 27(6):1083–1096.

Meyerowitz, B. E. and Chaiken, S. (1987). The effect of message framing on breast self-examination attitudes, intentions, and behavior. *Journal of Personality and Social Psychology*, 52(3):500–510.

Meyvis, T. and Janiszewski, C. (2002). Consumers' beliefs about product benefits: The effect of obviously irrelevant product information. *Journal of Consumer Research*, 28(4):618–635.

Milgram, S. (1963). Behavioral study of obedience. *The Journal of Abnormal and Social Psychology*, 67(4):371–378.

Milkman, K. L., Rogers, T., and Bazerman, M. H. (2009). Highbrow films gather dust: Time-inconsistent preferences and online dvd rentals. *Management Science*, 55(6):1047–1059.

Milkman, K. L., Rogers, T., and Bazerman, M. H. (2010). I'll have the ice cream soon and the vegetables later: A study of online grocery purchases and order lead time. *Marketing Letters*, 21(1):17–35.

Milosavljevic, M., Navalpakkam, V., Koch, C., and Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, 22(1):67–74.

Miravete, E. J. (2003). Choosing the wrong calling plan? ignorance and learning. *The American Economic Review*, 93(1):297–310.

Mohr, G. S., Lichtenstein, D. R., and Janiszewski, C. (2012). The effect of marketer-suggested serving size on consumer responses: The unintended consequences of consumer attention to calorie information. *Journal of Marketing*, 76(1):59–75.

Moore, D. A. and Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, 115(2):502–517.

Morwitz, V. G., Greenleaf, E. A., and Johnson, E. J. (1998). Divide and prosper: Consumer's reactions to partitioned prices. *Journal of Marketing Research*, 35:453–463.

Muchnik, L., Aral, S., and Taylor, S. J. (2013). Social influence bias: a randomized experiment. *Science*, 341(6146):647–651.

Narayanan, S. and Manchanda, P. (2012). An empirical analysis of individual level casino gambling behavior. *Quantitative Marketing and Economics*, 10(1):27–62.

Neumann, N. and Böckenholt, U. (2014). A meta-analysis of loss aversion in product choice. *Journal of Retailing*, 90(2):182–197.

Neumann, N., Böckenholt, U., and Sinha, A. (2016). A meta-analysis of extremeness aversion. *Journal of Consumer Psychology*, 26(2):193–212.

Odean, T. (1999). Do investors trade too much? *American Economic Review*, 89(5):1279–1298.

Orquin, J. L., Bagger, M. P., and Loose, S. M. (2013). Learning affects top down and bottom up modulation of eye movements in decision making. *Judgment and Decision Making*, 8(6):700–716.

Orquin, J. L., Chrobot, N., and Grunert, K. G. (2018). Guiding decision makers' eye movements with (un)predictable object locations. *Journal of Behavioral Decision Making*, 31(3):341–354.

Orquin, J. L. and Loose, S. M. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, 144(1):190–206.

Paetz, F. and Guhl, D. (2017). Understanding differences in segment-specific willingness-to-pay for the fair trade label. *Marketing ZFP - Journal of Research and Management*, 39(4):37–46.

Paetz, F. and Steiner, W. (2017). The benefits of incorporating utility dependencies in finite mixture probit models. *OR Spectrum*, 39(3):793–819.

Palmatier, R. W., Houston, M. B., and Hulland, J. (2018). Review articles: purpose, process, and structure. *Journal of the Academy of Marketing Science*, 46(1):1–5.

Payne, J. W., Bettman, J. R., Coupey, E., and Johnson, E. J. (1992). A constructive process view of decision making: Multiple strategies in judgment and choice. *Acta Psychologica*, 80(1):107–141.

Phillips, D. M. and Baumgartner, H. (2002). The role of consumption emotions in the satisfaction response. *Journal of Consumer Psychology*, 12(3):243–252.

Pieters, R. and Warlop, L. (1999). Visual attention during brand choice: The impact of time pressure and task motivation. *International Journal of Research in Marketing*, 16(1):1–16.

Pope, D. G. and Schweitzer, M. E. (2011). Is tiger woods loss averse? persistent bias in the face of experience, competition, and high stakes. *American Economic Review*, 101(1):129–157.

Rabin, M. (1998). Psychology and economics. *Journal of Economic Literature*, 36(1):11–46.

Rabin, M. (2002). A perspective on psychology and economics. *European Economic Review*, 46(4):657–685.

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological Methodology*, 25:111–163.

Rao, V. R. (2014). *Applied Conjoint Analysis*. Springer, Berlin, Germany.

Rasouli, S. and Timmermans, H. (2015). Models of bounded rationality under certainty. In Rasouli, S. and Timmermans, H., editors, *Bounded Rational Choice Behaviour: Applications in Transport*, pages 1–30. Emerald Group Publishing Limited, Bingley, United Kingdom.

Read, D. and van Leeuwen, B. (1998). Predicting hunger: The effects of appetite and delay on choice. *Organizational Behavior and Human Decision Processes*, 76(2):189–205.

Reutskaja, E., Nagel, R., Camerer, C. F., and Rangel, A. (2011). Search dynamics in consumer choice under time pressure: An eye-tracking study. *American Economic Review*, 101(2):900–926.

Romani, S., Grappi, S., and Dalli, D. (2012). Emotions that drive consumers away from brands: Measuring negative emotions toward brands and their behavioral effects. *International Journal of Research in Marketing*, 29(1):55–67.

Rooderkerk, R. P., van Heerde, H. J., and Bijmolt, T. H. (2011). Incorporating context effects into a choice model. *Journal of Marketing Research*, 48(4):767–780.

Rossi, P., Allenby, G., and McCulloch, R. (2005). *Bayesian Statistics and Marketing*. Wiley, Hoboken, NJ.

Russell, G. J. (2014). Brand choice models. In Winer, R. S. and Neslin, S. A., editors, *The History of Marketing Science*, volume 3 of *World Scientific-Now Publishers Series in Business*, pages 19–46. World Scientific.

Sawtooth Software (2017). The CBC system for choice-based conjoint analysis, (Technical Report Version 9), Sawtooth Software, Inc., Orem, Utah.

Scarpa, R., Gilbride, T. J., Campbell, D., and Hensher, D. A. (2009). Modelling attribute non-attendance in choice experiments for rural landscape valuation. *European Review of Agricultural Economics*, 36(2):151–174.

Scarpa, R., Zanoli, R., Bruschi, V., and Naspetti, S. (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics*, 95(1):165–180.

Schlereth, C. and Skiera, B. (2017). Two new features in discrete choice experiments to improve willingness-to-pay estimation that result in SDR and SADR: Separated (adaptive) dual response. *Management Science*, 63(3):829–842.

Schmidt, K. M., Spann, M., and Zeithammer, R. (2015). Pay what you want as a marketing strategy in monopolistic and competitive markets. *Management Science*, 61(6):1217–1236.

Shi, S. W., Wedel, M., and Pieters, R. (2013). Information acquisition during online decision making: A model-based exploration using eye-tracking data. *Management Science*, 59(5):1009–1026.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1):99–118.

Simon, H. A. (1959). Theories of decision-making in economics and behavioral science. *American Economic Review*, 49(3):253–283.

Simonson, I. (1989). Choice based on reasons: The case of attraction and compromise effects. *Journal of Consumer Research*, 16(2):158–174.

Simonson, I. (2008). Will I like a “medium” pillow? another look at constructed and inherent preferences. *Journal of Consumer Psychology*, 18(3):155–169.

Simonson, I. and Tversky, A. (1992). Choice in context: Tradeoff contrast and extremeness aversion. *Journal of Marketing Research*, 29(3):281.

Soman, D. (1998). The illusion of delayed incentives: Evaluating future effort-money transactions. *Journal of Marketing Research*, 35(4):427–437.

Steiner, M., Eggert, A., Ulaga, W., and Backhaus, K. (2016). Do customized service packages impede value capture in industrial markets? *Journal of the Academy of Marketing Science*, 44(2):151–165.

Stenstrom, E. P., Saad, G., and Hingston, S. T. (2018). Menstrual cycle effects on prosocial orientation, gift giving, and charitable giving. *Journal of Business Research*, 84:82–88.

Stüttgen, P., Boatwright, P., and Monroe, R. T. (2012). A satisficing choice model. *Marketing Science*, 31(6):878–899.

Sunstein, C. R. (2015). The ethics of nudging. *Yale Journal on Regulation*, 32(2):413–450.

Svenson, O. (1981). Are we all less risky and more skillful than our fellow drivers? *Acta Psychologica*, 47(2):143–148.

Swait, J. and Adamowicz, W. (2001). The influence of task complexity on consumer choice: A latent class model of decision strategy switching. *Journal of Consumer Research*, 28(1):135–148.

Swait, J. and Ben-Akiva, M. (1987). Incorporating random constraints in discrete models of choice set generation. *Transportation Research Part B: Methodological*, 21(2):91–102.

Swait, J., Popa, M., and Wang, L. (2016). Capturing context-sensitive information usage in choice models via mixtures of information archetypes. *Journal of Marketing Research*, 53(5):646–664.

Tarrahi, F., Eisend, M., and Dost, F. (2016). A meta-analysis of price change fairness perceptions. *International Journal of Research in Marketing*, 33(1):199–203.

Thaler, R. H. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization*, 1(1):39–60.

Thaler, R. H. (1981). Some empirical evidence on dynamic inconsistency. *Economic Letters*, 8:201–207.

Thaler, R. H. (2016). Behavioral economics: Past, present, and future. *American Economic Review*, 106(7):1577–1600.

Thaler, R. H. (2018). Nudge, not sludge. *Science*, 361(6401):431.

Thomas, M. and Morwitz, V. G. (2005). Penny wise and pound foolish: The left-digit effect in price cognition. *Journal of Consumer Research*, 32(1):54–64.

Thurstone, L. L. (1927). Psychophysical analysis. *The American Journal of Psychology*, 38(3):368–389.

Toubia, O., De Jong, M. G., Stieger, D., and Füller, J. (2012). Measuring consumer preferences using conjoint poker. *Marketing Science*, 31(1):138–156.

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge, UK, 2 edition.

Trope, Y. and Liberman, N. (2000). Temporal construal and time-dependent changes in preference. *Journal of Personality and Social Psychology*, 79(6):876–889.

Tully, S. M. and Winer, R. S. (2014). The role of the beneficiary in willingness to pay for socially responsible products: A meta-analysis. *Journal of Retailing*, 90(2):255–274.

Tversky, A. (1969). Intransitivity of preferences. *Psychological Review*, 76(1):31–48.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, 79(4):281–299.

Tversky, A. (1974). Assessing uncertainty. *Journal of Royal Statistical Society. Series B (Methodological)*, 36(2):148–159.

Tversky, A. and Kahneman, D. (1971). Belief in the law of small numbers. *Psychological Bulletin*, 76(2):105–110.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, 185:1124–1131.

Van der Lans, R., Pieters, R., and Wedel, M. (2008). Eye-movement analysis of search effectiveness. *Journal of the American Statistical Association*, 103(482):452–461.

Van Loo, E. J., Nayga, R. M., Campbell, D., Seo, H.-S., and Verbeke, W. (2018). Using eye tracking to account for attribute non-attendance in choice experiments. *European Review of Agricultural Economics*, 45(3):333–365.

VanEpps, E. M., Downs, J. S., and Loewenstein, G. (2015). Advance ordering for healthier eating? field experiments on the relationship between time delay and meal content. *Journal of Marketing Research*, 53(3):369–380.

Vohs, K. D. and Faber, R. J. (2007). Spent resources: Self-regulatory resource availability affects impulse buying. *Journal of Consumer Research*, 33(4):537–547.

Voleti, S., Srinivasan, V., and Ghosh, P. (2017). An approach to improve the predictive power of choice-based conjoint analysis. *International Journal of Research in Marketing*, 34(2):325–335.

Wedel, M. (2018). Improving ad interfaces with eye tracking. In Norman, K. L. and Kirakowski, J., editors, *The Wiley Handbook of Human Computer Interaction*, volume 2, chapter 41, pages 889–907. John Wiley & Sons.

Wedel, M. and Kamakura, W. A. (2000). *Market Segmentation: Conceptual and Methodological Foundations*. Springer Science & Business Media, New York.

Wedel, M. and Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6):97–121.

Wedel, M. and Pieters, R. (2008). Eye tracking for visual marketing. *Foundations and Trends in Marketing*, 1(4):231–320.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology*, 39(5):806.

Wertenbroch, K. (1998). Consumption self-control by rationing purchase quantities of virtue and vice. *Marketing Science*, 17(4):317–337.

Windschitl, P. D. and Stuart, J. O. (2015). Optimism biases. In Keren, G. and Wu, G., editors, *The Wiley Blackwell Handbook of Judgment and Decision Making*, chapter 15, pages 431–455. John Wiley & Sons, Ltd.

Wood, S. L. (2001). Remote purchase environments: The influence of return policy leniency on two-stage decision processes. *Journal of Marketing Research*, 38(2):157–169.

Yadav, M. S., de Valck, K., Hennig-Thurau, T., Hoffman, D. L., and Spann, M. (2013). Social commerce: A contingency framework for assessing marketing potential. *Journal of Interactive Marketing*, 27(4):311–323.

Yadav, M. S. and Pavlou, P. A. (2014). Marketing in computer-mediated environments: Research synthesis and new directions. *Journal of Marketing*, 78(1):20–40.

Yang, L. C., Toubia, O., and De Jong, M. G. (2015). A bounded rationality model of information search and choice in preference measurement. *Journal of Marketing Research*, 52(2):166–183.

Yang, L. C., Toubia, O., and de Jong, M. G. (2018). Attention, information processing, and choice in incentive-aligned choice experiments. *Journal of Marketing Research*, 55(6):783–800.

Yang, Y., Vosgerau, J., and Loewenstein, G. (2013). Framing influences willingness to pay but not willingness to accept. *Journal of Marketing Research*, 50(6):725–738.

Yaoyuneyong, G., Foster, J. K., and Flynn, L. R. (2014). Factors impacting the efficacy of augmented reality virtual dressing room technology as a tool for online visual merchandising. *Journal of Global Fashion Marketing*, 5(4):283–296.

Yegoryan, N., Guhl, D., and Klapper, D. (2020). Inferring attribute non-attendance using eye tracking in choice-based conjoint analysis. *Journal of Business Research*, 111:290–304.

Zeelenberg, M. and Pieters, R. (1999). Comparing service delivery to what might have been. *Journal of Service Research*, 2(1):86–97.

Zervas, G., Proserpio, D., and Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of Marketing Research*, 54(5):687–705.

Zhang, J. and Krishnamurthi, L. (2004). Customizing promotions in online stores. *Marketing Science*, 23(4):561–578.